The Benefits of Uncertain Instruction

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ABSTRACT

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This dissertation describes two studies that empirically test instructional methods designed to promote learning, transfer, and curiosity in the context of real-world science classrooms. In the first study, I compared an inherently uncertain form of instruction to an inherently certain one, and in the second study, I compared different levels of uncertainty within the same inherently uncertain instruction type. The first study demonstrates that, compared to an inherently certain form of instruction (tell-then-practice), the inherently uncertain form of instruction (Invention) produced greater curiosity and transfer, which may reflect deeper learning. While this study showed promising results, it revealed additional questions, which were answered by the second study. Specifically, because there were differences other than uncertainty between conditions, I could not fully conclude that uncertainty is what caused group differences in curiosity or transfer. To confirm that it is, in fact, uncertainty influencing curiosity and transfer, the second study examined learning activities that were more similar to one another, but still differed in uncertainty. Specifically, I compared two Invention conditions, in which one group of students was given more information prior to invention than the other. This manipulation also showed that higher uncertainty led to greater curiosity and transfer. The research in this dissertation also examines how uncertainty influences affect and whether state-level curiosity influences learning and transfer. Further, it shows how curiosity changes over time and demonstrates a new way to behaviorally and qualitatively measure curiosity.

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Chapter 1: Introduction

"Curiosity in children is but an appetite after knowledge and ought to be encouraged in them, not only as a good sign, but as the great instrument nature has provided to remove that ignorance they were born with …" – John Locke, *Some Thoughts Concerning Education* (1693)

Psychological research, while varying in operational definitions of curiosity, appears largely to agree with Locke's notion. Curiosity has been shown to be associated with cognitive, social, and emotional development across the lifespan (Keller, Schneider, & Henderson, 1994), as well as identity formation and learning (Erikson, 1968). In fact, Jean Piaget suggested that being curious is a *prerequisite* for knowledge construction (Keller et al., 1994). In line with these ideas, many curricula and education standards have explicitly aimed to foster curiosity (e.g., The University of Chicago Laboratory School science curriculum) (Jirout & Klahr, 2012). For example, the National Association for the Education of Young Children (NAEYC, 2011), included three curiosity criteria for assessing preschool programs. Similarly, the National Education Goals Panel (NEGP, 1995), referred to "openness and curiosity about new tasks and challenges" as an indicator of school readiness (Kagan, Moore, & Bredekamp, 1995, p. 23) and claimed that a lack of curiosity puts kids at risk of school failure. Additionally, several universities, such as Princeton University and the University of Manchester, have prioritized curiosity as a tenant of their missions (Engel, 2009). The American Association for the Advancement of Science (AAAS, 1993, 2008) even trains teachers to implement procedures meant to increase students' curiosity.

Yet, as I am sure many students, teachers, and educational researchers would agree, the typical formal education experience seems to be students who appear bored, are either passively listening to a lecture or taking notes, and are aiming to get just enough information to achieve a

certain grade or pass a test. Even if the content of a class might be fascinating, often the structure of a traditional lesson does not promote curiosity. In fact, it has been suggested that the current education system may be suppressing curiosity (Engel, 2013; Jirout, Vitiello, & Zumbrunn, 2018). This disheartening observation has motivated me to conduct research that answers the following general question: "How can we teach students in a way that will make them curious?"

One common theme across research on curiosity is that uncertainty is a key factor for fostering curiosity. Some studies have drawn students' attention to uncertainty (e.g. Fisher, HirshPasek, Newcombe, & Golinkoff, 2013; Markey & Loewenstein, 2014; Weisberg et al., 2016). Others induced uncertainty by lessening the obviousness of the target response choice (e.g. Berlyne, 1962; Boykin & Harackiewicz, 1981), increasing the number of possible choices (e.g. Berlyne, 1962), making outcomes unknown (e.g. Hsee & Ruan, 2016), demonstrating outcomes of events that are contradictory to one's expectations (e.g. Stahl & Feigenson, 2015), providing stories with outcomes contradictory to what would be expected (e.g. Campion, Martins & Wilhelm, 2009**)**, or withholding information about content or process (e.g. Campion et al., 2009; Cyr, 1996; Loibl & Rummel, 2014). In all of these cases, compared to lower uncertainty conditions, participants demonstrated higher curiosity. It stands to reason, then, that inducing some uncertainty into instruction should lead to higher curiosity, and supposedly, greater learning.

However, the literature largely overlooks learning and ignores transfer, the ability to apply learned knowledge and skills to novel contexts (Klahr & Chen, 2011). Additionally, curiosity research with direct application to real-world classrooms, especially concerning exploratory learning paradigms, is limited. Further, studies measuring uncertainty's effect on curiosity tend not to measure affect, which is surprising because uncertainty is often

conceptualized as negative affect (Bar-Anan, Wilson, & Gilbert, 2009; Hirsh, Mar, & Peterson, 2012), and negative affect has been shown to be detrimental to learning and performance (Beal, Weiss, Barros, & MacDermid, 2005; Ellis & Ashbrook, 1988; Ellis, Ottaway, Varner, Becker, & Moore, 1997; Greene, Rucker, Zauss, and Harris, 1998; Howell & Conway, 1992; Pekrun, Lichtenfeld, Marsh, Murayama, & Goetz, 2017; Sarason, Sarason, & Pierce, 1990; Seibert & Ellis, 1991). This led me to conduct two studies empirically exploring the effect of uncertainty in instruction on curiosity, learning, transfer, and affect. Both studies examined uncertainty in the context of exploratory learning paradigms in real-world science classrooms. The first paper, which is currently under a second round of review at *Contemporary Educational Psychology*, compares an inherently uncertain form of instruction to an inherently certain form of instruction, and the second paper compares different levels of uncertainty within the same inherently uncertain instruction type.

In the study in the first paper, I compared tell-then-practice instruction, in which students were given all the information they needed to solve given problems (no uncertainty) to Invention instruction (high uncertainty), in which problem-relevant information was initially withheld and given only after students finished problem-solving. Additionally, for students who Invented, I provided only some students with expectations of uncertainty to test whether expecting uncertainty would mitigate the negative effect that uncertainty could have on affect. While this study found some promising results, it had some limitations and revealed additional questions that were address by the second paper. The biggest limitation in the study in the first paper was that because there were differences other than uncertainty between conditions, I could not fully conclude that it was uncertainty that caused the differences in curiosity or transfer outcomes. Specifically, students who completed the Invention activity were more actively involved in

learning because they had to generate their own ideas, compared to students who listened to the lecture and then completed practice problems. This could have led the groups that invented to feel more curious than the other group, independent of uncertainty. These differences in level of active involvement could have also caused differences in transfer between conditions. Additionally, due to the nature of comparing Invent-then-tell to tell-then-practice, the groups also differed in time between instruction and posttest and timing of curiosity measurement.

To remove differences other than uncertainty between conditions and to address concerns about timing, the study in the second paper examined learning activities that were more similar to one another, but still differed in level of uncertainty. Specifically, in this study two groups both participated in Invention instruction. However, one group of students was given task-relevant information prior to invention, and one group was given task-irrelevant information prior to invention. By having both groups invent with differing prior knowledge, I manipulated uncertainty, without creating other differences between groups as in the previous study. Therefore, in this study, I was able to eliminate the possibility that results were due to differences in the level of active involvement, differences in time between instruction and posttest, and differences in timing of measuring curiosity. Along with eliminating these limitations, the second study also examined uncertainty and curiosity over time, measured curiosity behaviorally, and used a more robust measure of uncertainty. Table 1 summarizes the main differences between the two studies. The following two chapters give detailed accounts of the methods and results of both studies.

Table 1. Main Differences between Paper 1 and Paper 2

Paper 1	**Paper 2**
Invent-then-Tell (High Uncertainty) compared to Tell-then-Practice (No Uncertainty)	Invention with High Uncertainty compared to Invention with Low Uncertainty
Tested the effect of expectations of uncertainty vs. no expectations of uncertainty on affect	No expectations of uncertainty given to either group
Curiosity measured via survey	Curiosity measured via survey and behavioral "question worksheet"
Hypotheses about curiosity and uncertainty overall	Hypotheses about curiosity and uncertainty over time
Uncertainty measured with 2 binary questions	Uncertainty measured with 5 Likert scale questions

Chapter 2: Developing a Thirst for Knowledge: How Uncertainty in the Classroom Influences Curiosity, Affect, Learning, and Transfer (Paper 1)

Abstract

Uncertainty is a key variable in fostering curiosity, which, in turn, is associated with learning. Yet, research in educational contexts rarely takes uncertainty into account, and rarely explores uncertainty and curiosity in the context of complex instructional activities. One concern with uncertainty is that it can provoke negative affect. Providing learners with expectations of future uncertainty may attenuate their feelings of negative affect. In a study with 138 middle school students learning physics concepts, I examined the relationship between uncertainty, curiosity, learning, transfer, and affect. Some students were given an inherently uncertain form of instruction, called Invention, in which information on how to solve the problem was initially withheld, while others were given direct instruction with all the necessary information to solve similar problems beforehand (No Uncertainty condition). Some of the students receiving uncertain instruction were given expectations about feeling uncertain (Expected Uncertainty condition), and some were not (Unexpected Uncertainty condition). Students in the unexpected uncertainty condition were the most curious, while students in the no uncertainty condition were the least curious. However, giving expectations of uncertainty reduced students' negative affect. All groups learned the content equally well, but the expected and unexpected uncertainty groups exhibited greater transfer. Further, positive affect predicted learning, above and beyond condition, and curiosity predicted transfer, but not above and beyond condition. This study extends existing research on uncertainty and curiosity by studying these constructs in real classrooms, in the context of an exploratory learning paradigm, and by considering curiosity's effect on transfer, rather than just learning. This work also demonstrates a practical approach for

educators to foster students' curiosity and transfer.

Keywords: uncertainty, curiosity, affect, learning, transfer, Invention

Uncertainty, a lack of predictability in an environment (Mushtaq, Bland, & Schaefer, 2011) or ambiguity of a task (Alison, Power, van den Heuvel, & Waring, 2015), is a key variable for fostering curiosity (Edleman, 1997). Curiosity, a desire to know, see, or experience (Berlyne, 1960; Litman & Spielberger, 2003; Loewenstein, 1994) that is often caused by feeling that one is lacking information or coherence (Berlyne, 1950, 1955), has notably been declared by Piaget (1952) as a prerequisite for knowledge construction. Therefore, it stands to reason that inducing some level of uncertainty into lessons could lead to increased curiosity and thereby, increased learning and transfer, making uncertainty an important construct to study in the context of education. In this paper, I describe a classroom study comparing uncertain and certain forms of learning activities and explore how they influence curiosity, affect, learning, and transfer.

Curiosity

Curiosity is elusive and hard to define (Jirout & Klahr, 2012). However, most definitions of curiosity describe it as a need for knowledge or information and the motivation to pursue it through exploration (Grossnickle, 2016). Another way to define curiosity is to distinguish it from related constructs, such as interest, which is "a psychological state of attention and affect toward a particular object or topic, and an enduring predisposition to reengage over time" (Harackiewicz, Smith, & Priniski, 2016). Whereas interest is driven by the goal of pursuing engagement and enjoyment with the object of one's interest, curiosity is driven by the goal of seeking resolution or filling a specific knowledge gap (Grossnickle, 2016; Renninger & Hidi, 2016). While interest can occur when one has either low or high levels of knowledge, curiosity occurs when one has *some* information but still identifies a knowledge gap (Grossnickle, 2016; Loewenstein, 1994; Schmitt & Lahroodi, 2008).

Furthermore, curiosity is a multidimensional construct; people can be curious about various entities, such as their physical surroundings, sensory stimuli, social interactions, or knowledge (Berlyne, 1954; Dewey, 1910; Grossnickle, 2016; Litman & Spielberger 2003; Litman, Collins, & Spielberger, 2005; Renner, 2006). Curiosity can be further construed as either a long-term trait or a short-term state, triggered by environmental variables.

In this paper, I study curiosity as a momentary state, rather than a long-term personal trait, because short-term instructional interventions are more likely to affect in-the-moment curiosity. In addition, I focus on cognitive curiosity, also known as intellectual curiosity, epistemic curiosity, or information-seeking curiosity, which is the desire for new knowledge (Berlyne, 1954; Berlyne, 1966; Grossnickle, 2016; Kang et al., 2009; Litman, 2010; Tripathi, Sarkate, Jalgaonkar, & Rege, 2015). For instance, a cognitively curious student, upon noticing that he does not have sufficient knowledge to solve a problem (see Golman & Loewenstein, 2018; Loewenstein, 1994), may ask his teacher many questions about the problem or search online for helpful information. Cognitive curiosity has direct implications for learning. That is, if students are motivated to seek information to fill knowledge gaps, they are likely to learn more.

Uncertainty Fosters Curiosity

Many theories describe how uncertainty fosters curiosity. For example, curiosity-drive theory explains that curiosity is aroused when people feel uncertain (Berlyne, 1954; Dashiell, 1925). In these situations, individuals experience uncertainty as an unpleasant state (Jirout & Klahr, 2012) and therefore, become motivated to reduce the uncertainty through information-seeking behaviors that allow them to gain knowledge of the unfamiliar (James, 1950). Through this search for information, individuals aim to reduce uncertainty and regain coherence in their thoughts and understanding. Similarly, Hebb's (1955) incongruity theory explains that people

have an innate sense-making desire that gets triggered when occurrences in their environment do not match their expectations of what would happen. Piaget's (1952) cognitive disequilibrium theory coincides with this notion. According to Piaget's theory, as children develop, they discover new information and experiences that are discrepant with what they already know. This information is uncertain and surprising, leading the child to be curious about it. In the same vein, Loewenstein's (1994) information-gap model of curiosity explains that when individuals experience an information gap, defined as "specific uncertainty that one is aware of" they desire knowledge to fill that gap (Golman & Loewenstein, 2018). While these four seminal theories differ in their approach to uncertainty, all agree that uncertainty fosters curiosity, and thus, uncertain forms of pedagogy may pique curiosity.

In addition, several empirical studies demonstrate that uncertainty provokes curiosity. For example, classroom studies show that drawing a student's attention to uncertainty by asking guiding questions to help the student recognize what she does not know or pointing out incomplete information, for example, leads to increased curiosity (e.g. Fisher, HirshPasek, Newcombe, & Golinkoff, 2013; Markey & Loewenstein, 2014; Weisberg, Hirsh-Pasek, Golinkoff, Kittredge, & Klahr, 2016). Further, lab studies with adults show that increasing uncertainty by decreasing the predictability of a target response (by lessening the obviousness of the correct choice, increasing the number of possible choices, or making outcomes unknown) leads to higher reported curiosity (e.g. Berlyne, 1962; Boykin & Harackiewicz, 1981; Hsee & Ruan, 2016). Additionally, inducing uncertainty by demonstrating outcomes of events that are contradictory to one's expectations leads to higher curiosity in both infants and adults, as demonstrated through reports of "wanting to know more" and behavioral evidence of increased exploration (e.g. Campion, Martins, & Wilhelm, 2009; Stahl & Feigenson, 2015). For example,

Campion et al. (2009) gave one group of undergraduates stories that contained outcomes contradictory to what would be expected based on the premise of the story, and another group certain stories that included no such contradiction. They found that students who read the uncertain stories wanted to know more about the stories once they were done reading them.

This pattern of increased curiosity in uncertain conditions has also been found when uncertainty was created by a lack of information about content (e.g. Campion et al., 2009; Loibl & Rummel, 2014) or process (e.g. Cyr, 1996; Loibl & Rummel, 2014). For instance, Campion et al. (2009) repeated their experiment with a different set of stories, either with or without missing explanations. Again, students reading uncertain stories (i.e. missing information) reported more curiosity than their peers. In a classroom study, Loibl and Rummel (2014) gave a group of students direct instruction about variance and then asked them to solve practice problems. Another group completed the problems *before* receiving direct instruction – an inherently uncertain condition because students lacked information about how to solve the problems. Before receiving direct instruction, this group reported higher curiosity than the group that received the certain, direct instruction right away. Similarly, in a classroom study of community college students learning about the moment of inertia, students in two groups viewed demonstrations of objects being rolled down a ramp. One group participated in predict-observe-explain, which was inherently uncertain because students were asked to make predictions about the order in which the objects would reach the bottom of the ramp without initially being given content material. The other group received direct instruction; they were told the order in which the items would go down the ramp and why. These students had all the information they needed to understand the demonstrations, thus having no uncertainty. The inherently *uncertain* pedagogy (predict-observe-explain) led to greater curiosity compared to inherently *certain* direct

instruction. Additionally, curiosity served as a strong predictor of learning, independent of condition.

As a whole, these studies suggest that uncertainty can be manipulated in multiple ways and still lead to positive changes in reported and behavioral curiosity, across several age groups and settings. This small body of work is encouraging because it shows uncertainty's potential for fostering curiosity. However, this review points to several gaps in the research. First, very little research comparing conditions of uncertainty to conditions of certainty has been done directly in classrooms. Classroom research focuses on drawing a student's attention to uncertainty (e.g. Fisher et al., 2013; Markey & Loewenstein, 2014; Weisberg et al., 2016), but rarely compares inherently uncertain instruction to more certain instruction. Overall, research relating uncertainty to curiosity mostly occurs in well-controlled lab studies that do not necessarily reflect a real-world environment. Second, most of the reviewed studies require participants to complete straightforward, well-structured tasks (i.e. press a button, choose an option, read a story). However, inherently uncertain instruction often involves exploratory problems with unclear goals or insufficient information to solve them (Sinnott, 1989; Voss & Post, 1988). Yet, aside from Cyr's (1996) case study and Loibl and Rummel's (2014) empirical study, research on the relationship between uncertainty and curiosity does not address less structured instructional paradigms such as inquiry, discovery, or exploratory problem solving, which are growing in popularity (e.g. Barrett & Moore, 2010; Hung & Loyens, 2012; Schwartz, Mennin, & Webb, 2001). Third, while the described theories and studies examine the role of uncertainty in curiosity, they do not test whether curiosity is associated with learning. Therefore, efforts to study the uncertainty-curiosity-learning relationship in academic settings are needed.

Curiosity, Learning, and Transfer

The uncertainty-curiosity-learning relationship is especially important because theory and research point to curiosity facilitating learning. For example, those with secure attachment styles tend to be curious about their environments and therefore, explore them more. This leads them to learn more about their environments (Voss & Keller, 1983). Similarly, in Erikson's (1950) theory of psychosocial development, adolescents who are more curious about possible social roles will learn more about them, leading them to select appropriate roles that fit their interests and abilities. In the same vein, Reio, Petrosko, Wiswell, and Thongsukmag (2006) explain that curiosity leads individuals to engage in information-seeking behaviors, which fosters knowledge construction.

These theories have been substantiated with empirical research, which shows that curiosity as an individual trait is associated with greater retention, learning, achievement, and intelligence. For instance, highly curious children have been shown to have greater recall of their learning experiences in a virtual art museum (Arnone, Grabowski, & Rynd, 1994) and of science-based texts they have read (e.g. Ainley, Hidi, & Berndorff, 2002), compared to their less curious peers. Moreover, teachers' ratings of their students' curiosity are positively correlated with students' scores on standardized academic achievement tests, including reading, math, grammar, and spelling (Alberti & Witryol, 1994). In a study of 6,200 kindergarteners, parents' ratings of their children's curiosity positively predicted reading and math achievement, even after controlling for several factors, such as socioeconomic status (Shah, Weeks, Richards, & Kaciroti, 2018). In fact, in a meta-analysis of traits affecting academic achievement, curiosity was a direct, correlated predictor of academic performance, and the additive effect of curiosity and effort rivaled that of intelligence (von Stumm, Hell, & Chamorro-Premuzic, 2011).

However, there is relatively little research on the relationship between *state* curiosity and learning. In one example, adult participants learned more answers to trivia questions that made them more curious compared to questions they were not so curious about (Kang et al., 2009). Gruber, Gelman, and Ranganath (2014) demonstrated the same and also found that participants learned more faces that were presented during periods of high curiosity than those presented during low-curiosity trials. Likewise, in a study of community college students learning physics, in-the-moment curiosity positively predicted learning (Lamnina & Chase, 2017).

Overall, these studies allow us to reasonably conclude that curiosity is important for learning and academic success. However, few studies have explored the connection between uncertainty, curiosity, and learning in academic settings, and research has largely overlooked state curiosity, which perhaps can be more readily influenced than trait curiosity (Grossnickle, 2016). Moreover, curiosity research tends to ignore curiosity's effect on transfer. While research has examined curiosity's effect on *learning*, conceptualized as recognition, recall, and school achievement, I know of no studies that explore the relationship between curiosity and transfer.

Transfer is the ability to take knowledge and skills learned in one context and apply or extend them in a novel context (Klahr & Chen, 2011). A key goal of schooling is to prepare children for the world beyond school. Thus, transfer is a critical outcome of classroom education. Research suggests that while transfer is relatively rare (Detterman, 1993; Gick & Holyoak, 1983), it can occur when people learn content deeply (Bransford, Brown, & Cocking, 2000), like they might when they are highly curious. Thus, I predict that curiosity will be positively related to transfer outcomes.

Concerns About the Relationship Between Uncertainty and Affect

Since a goal of this research is to increase curiosity by increasing uncertainty of instruction, it is also important to explore other outcomes uncertainty may have. The reviewed theories and research provide evidence that uncertainty increases curiosity, which can influence learning. However, uncertainty can also increase negative affect (Bar-Anan, Wilson, & Gilbert, 2009). In fact, prior research and theory about uncertainty have conceptualized uncertainty as an aversive state, characterized by negative affect that individuals are motivated to reduce (Bar-Anan et al., 2009). For instance, the entropy model of uncertainty suggests that uncertainty is experienced as a state of anxiety and affective instability (Hirsh, Mar, & Peterson, 2012). This is further supported by neuroscientific research, which shows that highly uncertain stimuli activate brain regions associated with conflict and arousal, and reduction of uncertainty is accompanied by activation of brain regions associated with reward processing (Gruber et al., 2014; Jepma, Verdonschot, van Steenbergen, Rombouts, & Nieuwenhuis, 2012; Kang et al., 2009). Thus, the presence of uncertainty can feel negative and the reduction of uncertainty can feel positive.

In academic settings, uncertainty can lead to negative affect for multiple reasons, depending on students' focus. When a lack of information prohibits them from finding a correct solution, students could experience negative *epistemic emotions*, if their focus is on the uncertainty of the problem, or negative *achievement emotions*, if their focus is on their personal failure (Pekrun & Linnenbrink-Garcia, 2014). This could be problematic in learning contexts because negative affect leads to self-preoccupying thoughts, which interfere with focusing attention on the task at hand, resulting in lowered task performance (Beal, et al., 2005; Ellis & Ashbrook, 1988; Ellis, Ottaway, Varner, Becker, & Moore, 1997; Sarason, Sarason, & Pierce, 1990). Likewise, negative affect can slow down the rate of skill acquisition (Greene, Rucker,

Zauss, & Harris, 1998) and increase task-irrelevant thoughts and cognitive interference (Howell & Conway, 1992; Seibert & Ellis, 1991). It can also negatively predict grades and test scores (Pekrun, Lichtenfeld, Marsh, Murayama, & Goetz, 2017).

There is little research addressing the link between uncertainty and positive affect. However, in one study, positive affect led individuals to involve themselves in skill-based activities and increased their desire for more learning (Kashdan, Rose, & Fincham, 2004). Further, Gable and Haromon-Jones (2010) explain that positive affect leads individuals to generate solutions that require broader, deeper thinking beyond their immediate context. Another study shows that positive affect positively predicts grades and test scores (Pekrun et al., 2017). Moreover, instruction that supports positive affect is correlated with more effective cognitive processing (Hinton, Miyamoto, & Della-Chiesa, 2008).

So, while uncertainty can increase curiosity, which would be beneficial for learning, it can also increase negative affect, which could be detrimental to learning. A potential reason for this paradox is that research establishing these claims does not consider uncertainty's two forms: expected and unexpected (Yu & Dayan, 2005). Expected uncertainty occurs when the unpredictability of a given situation is well-known. For instance, individuals who rely on train transportation often account for the unpredictability of train schedules by factoring in additional travel time. In contrast, unexpected uncertainty occurs when unpredictable changes affect the environment and violate preconceived notions. Unexpected uncertainty would occur in the aforementioned example if trains typically adhered to a specific, accurate schedule, and then suddenly were delayed due to an accident that commuters could not anticipate. Differences in the affect provoked by these two types of uncertainty have yet to be examined. And yet, expectations about a negative event can lead to affective attenuation, such that bad outcomes feel better when

they are expected (Shepperd & McNulty, 2002). Therefore, it is possible that giving expectations of uncertainty could ameliorate the effect of uncertainty on negative affect. Thus, I could use *expected* uncertainty as a tool for fostering curiosity, without increasing students' negative affect.

The Present Study

To my knowledge, there has yet to be a classroom study combining uncertainty, curiosity, learning, and transfer into one model. Additionally, research on the connection between curiosity and academic success has typically considered curiosity as a trait, rather than a state that could be influenced with instruction. Further, aside from Loibl and Rummel (2014) and Lamnina and Chase (2017), research on both uncertainty and curiosity in academic settings tends to overlook more complex instructional activities, such as exploratory problem solving. Also, research has yet to examine differences between expected and unexpected uncertainty on affect. The goal of the present research was to address these gaps. Particularly, I tested the notion that inherently uncertain instruction increases students' in-the-moment curiosity, which, in turn, may influence learning and transfer. I also directly tested whether giving students expectations about the uncertain pedagogy would make a difference in their affect, and whether subsequent differences in affect influence learning and transfer.

In the current study, some students were challenged to complete inherently uncertain Invention activities (Schwartz & Martin, 2004), in which they invented their own formulas for scientific concepts. This activity was uncertain because students were given no prior content information or direct instruction for how to "invent a formula." Thus, the task was ambiguous and the correctness of their formula was unpredictable. This was followed by a short lecture on the relevant formulas and concepts. I contrasted this condition with a "No Uncertainty" condition, in which students completed comparable activities *after* viewing the lecture in a more

traditional tell-and-practice format. This condition was certain because students were given the formula and an explanation of the related concepts to start. Instead of inventing, they were practicing applying a formula to the same set of problems and observing them in the simulation, and thus, experienced no ambiguity or unpredictability. Further, to examine how expectations about this uncertainty impacted students' affect, for some of the students who invented, I explained that the activities they were going to do would be uncertain, and for some of the students I did not. Thus, the study contrasted three conditions: No Uncertainty, Expected Uncertainty, and Unexpected Uncertainty.

We specifically chose Invention activities as my uncertain form of instruction because when designing for curiosity, it is important to give students the opportunity to *practice* seeking out information and expressing curiosity by engaging in more active ways (Jirout, Vitiello, & Zumbrunn, 2018). Because Invention requires students to explore and iterate, it readily lends itself to this kind of research. Additionally, prior research shows that Invention activities lead students to notice gaps in their knowledge (Loibl, Roll, & Rummel, 2017), which is key to triggering curiosity (Loewenstein, 1994). Further, Invention, followed by direct instruction, enhances students' ability to transfer compared to more traditional forms of instruction (e.g. Schwartz, Chase, Oppezzo, & Chin, 2011). I suspect that one reason for this is that Invention activities are more uncertain, which provokes learners' curiosity to learn from a later lecture.

Below, I summarize the study hypotheses:

(1) Students working in the Expected Uncertainty and Unexpected Uncertainty conditions will become more curious than those in the No Uncertainty condition. However, the Expected Uncertainty and Unexpected Uncertainty conditions should not differ in their curiosity levels.

(2) The No Uncertainty and Expected Uncertainty conditions will report similar levels of negative and positive affect. However, the Unexpected Uncertainty condition will report higher negative affect than the other conditions. I do not predict condition differences in positive affect.

(3) Students in the Expected and Unexpected Uncertainty conditions will learn and transfer more than students in the No Uncertainty group. Students in the Expected Uncertainty group will learn and transfer more than the Unexpected Uncertainty group, due to their (predicted) lower experience of negative affect.

(4) Regardless of condition, students' levels of curiosity will positively predict how much they learn and transfer.

(5) Regardless of condition, students' positive affect will positively predict their learning and transfer, while students' negative affect will negatively predict their learning and transfer.

Method

Participants

One-hundred thirty-eight students from five seventh-grade and five eighth-grade classes in a public middle school in New Jersey participated in this study during their regular hour-long science classes ($n_{ExpectedUncertainty} = 47$; $n_{UnexpectedUncertainty} = 42$, $n_{NoUncertainty} = 49$). Forty-one participants were classified by the school as honors students, 11 of them in Expected Uncertainty, 17 in Unexpected Uncertainty, and 13 in No Uncertainty conditions. These students were part of regular classes but were considered by the school to be higher performing. The school population consists of 89% Hispanic, 7% White, and 4% other ethnic backgrounds, and 78% of students are eligible for free or reduced-price lunch.

Instructional Content

In this study, students learned about physics concepts related to Hooke's Law and Newton's Second Law. These concepts are part of the "Motion and Stability: Forces and Interaction" Next Generation's Science Standard for grades 6-8 (NGSS, 2013). Hooke's Law (displacement = force/ spring constant) describes a spring's displacement as a function of the force applied and the spring constant, or the stiffness/stretchiness of the spring (Khan, 2008). Newton's Second Law (acceleration= force/mass) describes how the acceleration of an object is directly related to the net force acting upon it and inversely related to its mass (Khan, 2011). Both displacement and acceleration are mathematically expressed as ratios. A major goal of my instruction was to have students understand ratio structures, so they could transfer their understanding of these to new, ratio-based science formulas. Ratios are widespread in science, and many science subjects, such as physics, cannot be understood without understanding ratios (Bailey, Siegler, & Geary, 2014).

Procedure and Study Design

Students within each class were randomly assigned to one of three conditions: Expected Uncertainty (EU), Unexpected Uncertainty (UU), and No Uncertainty (NU), so that each class contained all conditions. The study took place over a total of four class periods (Figure 1). Students initially took a pretest (~20-30 minutes). Two weeks later, they worked independently for two class periods on learning activities specific to their condition (100 minutes total). During these two periods, students also completed curiosity and affect surveys and a brief manipulation check. Finally, all students took a posttest (~45 minutes). All sessions were led by the same experimenter, along with one to two other researchers who helped monitor the classroom. The

general sequence of activities within each condition was modeled after other studies of Invention (e.g. Chase & Klahr, 2017; Schwartz et al., 2011).

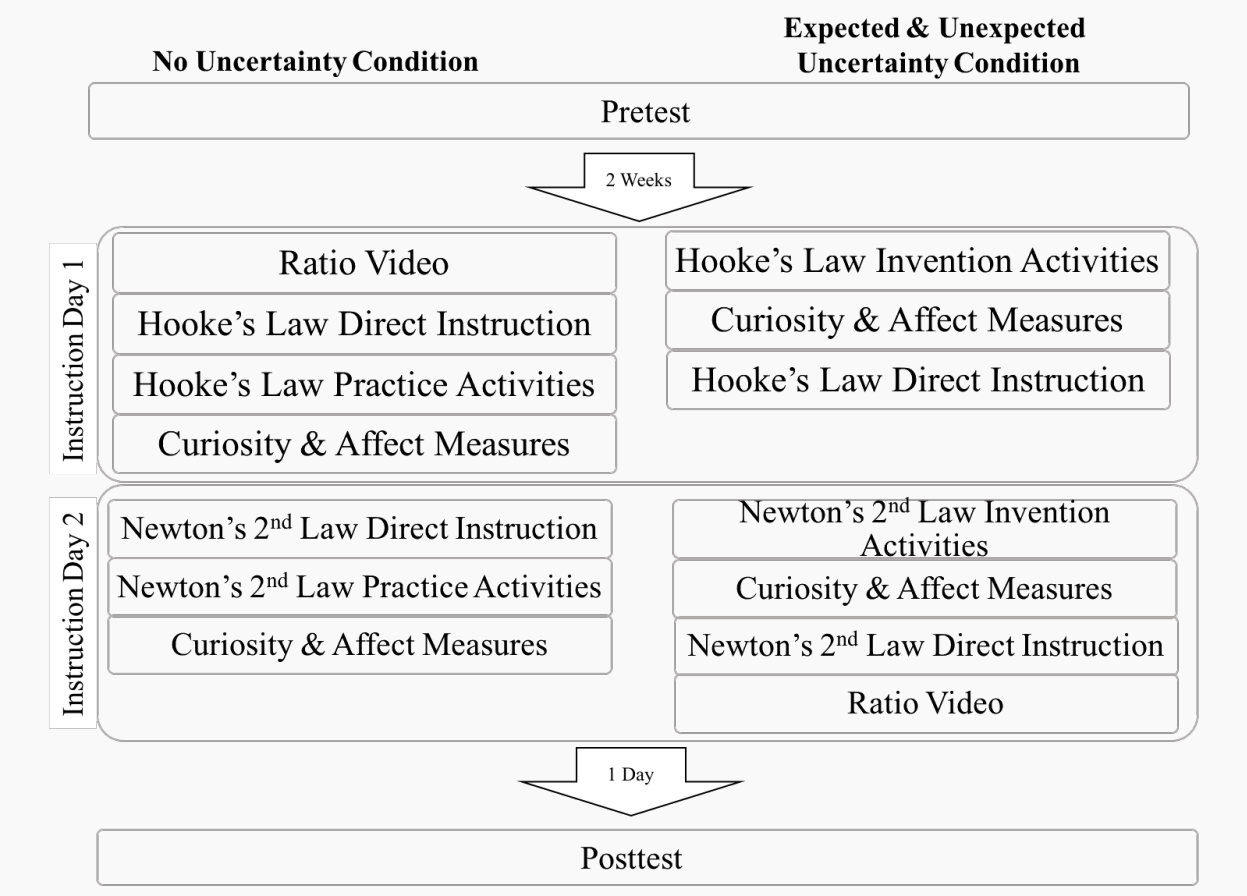


Figure 1. Study design and procedure.

No uncertainty condition.

In the NU condition, students were always given direct instruction on topics first, followed by problem-solving practice with the aid of a computer simulation. On the first day of instruction, the NU group watched the Ratio Video and the Hooke's Law Video, then completed three practice activities in which they applied the Hooke's Law equation to a variety of scenarios using a paper booklet and an online PhET simulation (PhET Interactive Simulations, 2017). Subsequently, they completed curiosity, affect, and manipulation check questionnaires. On the

second day of instruction, this procedure was repeated for Newton's Second Law (except the Ratio Video was not shown).

Expected uncertainty and unexpected uncertainty conditions.

In the EU and UU conditions, students received direct instruction *after* attempting to invent their own formulas. They first watched a video introducing the invention activities. For the EU group, this video included an additional 26-second segment providing expectations of uncertainty (e.g. "You should expect to feel uncertain in your answers and unsure of what you're doing…"). This was the only difference in procedure between the UU and EU groups.

Next, both groups worked on Invention activities. Afterwards, they completed curiosity, affect, and manipulation check questionnaires, then watched the Hooke's Law Video. For the NU group, I captured curiosity and affect *after* students were given the information they needed to understand the content, while for the EU and UU groups I captured curiosity and affect *before* students were told the information. This allowed us to measure curiosity that developed due to the main learning activity.

The next day, the procedure was repeated for Newton's Second Law. Then students watched the Ratio Video. This video was identical to the one watched by the NU group.

Materials

Direct instruction videos.

Students watched three short (~ 3 min) videos that delivered direct instruction. The Ratio Video provided a conceptual explanation of ratio and showed that both Hooke's and Newton's second laws rely on a ratio structure. The video also gave additional examples of ratio-based physical science concepts, such as density and speed.

The Hooke's Law video provided a conceptual explanation, the formula (displacement = force/ spring constant) and two worked examples of problems on Hooke's Law. Students also watched an isomorphic version of this video for Newton's Second Law.

Activities.

All participants completed three activities about Hooke's Law on Day 1 and isomorphic versions of these same activities about Newton's Second Law on Day 2 of instruction (below I give only examples of the Hooke's law version of the activities). For the NU group, the activities gave students practice in applying the formulas they learned in the Hooke's and Newton's second law videos in a variety of problem-solving scenarios. For the UU and EU groups, the activities guided students through the process of inventing formulas while continually evaluating and refining their formulas.

In the first activity, students worked on a worksheet of four contrasting cases (See Figure 2; Bransford, Franks, Vye, & Sherwood, 1989; Gibson & Gibson, 1955; Schwartz et al., 2011), which use systematic variation to highlight deep features (e.g. force, spring constant for Hooke's law). The NU group was asked to *apply* the Hooke's law formula to *each case to solve for displacement.* In contrast, the UU and EU groups were asked to invent a formula that would explain "how far a spring moves," then test it on each case. Students were told that if an example disconfirmed their formula, they should flip the page and invent a new formula to test, and repeat this process until they were successful.

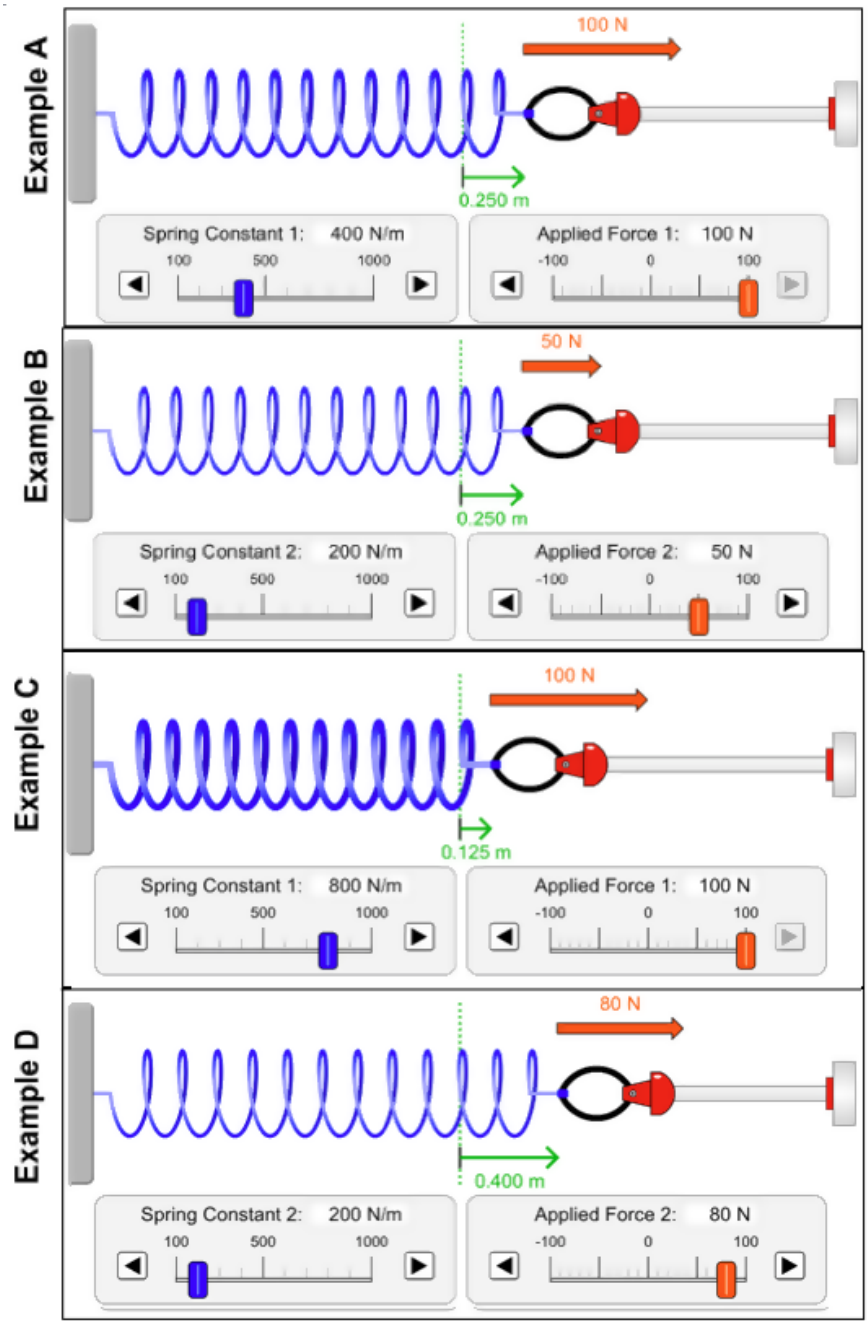


Figure 2. Contrasting cases used for Hooke's Law in activity 1.

In the second activity, students were given a worksheet of three examples where one of the variables' values was missing. Students were asked to use either Hooke's Law (NU group) or the formula they invented (EU and UU groups) to solve for the spring's displacement. Then students entered the given values into a simulation (Figure 3), to evaluate their calculated

solutions. If calculated answers did not match the simulated values, the NU group was instructed to check their work, and the EU and UU groups were instructed to come up with a new formula.

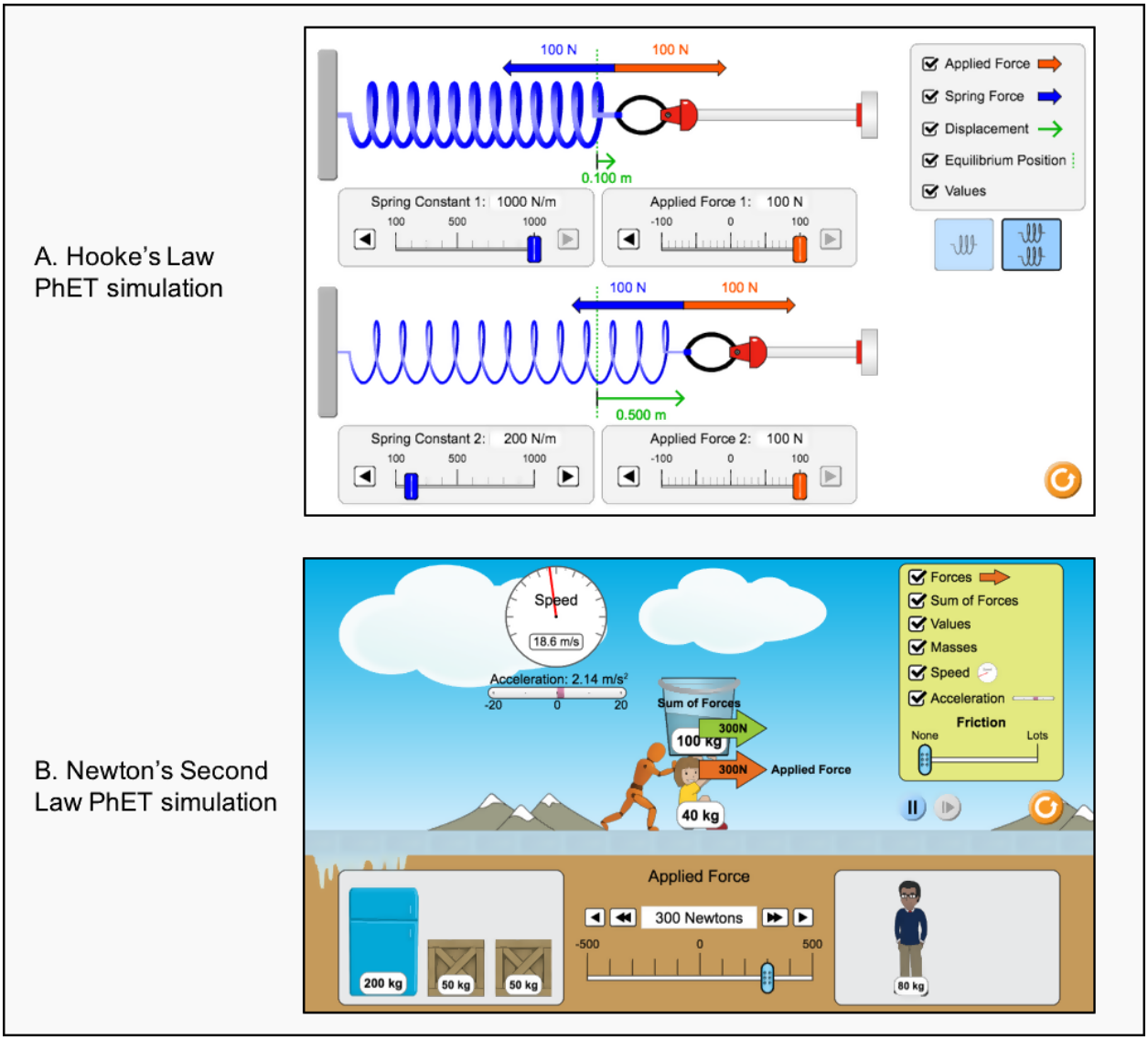


Figure 3. PhET simulations used in activities 2 and 3. A)Users can vary spring constant, force applied, or displacement. B)Users can vary mass and applied force, while observing the resultant acceleration. Images adapted from PhET Interactive Simulations (2017).

In the third activity, students were challenged to set up the simulation to show two different ways of displacing the spring 0.100m (e.g. 20N / 200N/m and 33N / 330N/m), then

check whether the simulated numbers equaled those calculated from either the formula they invented (EU and UU groups) or the formula they were taught (NU group).

Measures

Manipulation Check

To assess the success of my uncertainty manipulation, participants completed a 2-item questionnaire at the end of each intervention day. Items asked (1) "While you were working on the science activities today, did you feel uncertain?" and (2) "While you were working on the science activities today, were you unsure if your answers were correct?" Every "Yes" response was given 1 point and summed across questions and days, for a maximum of 4 points.

Curiosity

State-level cognitive curiosity was measured with an 8-item Likert scale questionnaire adapted from the state subscale of Naylor's (1981) State-Trait Curiosity Inventory. Participants responded to statements such as "I want to know more about what I just worked on," and "I feel like seeking information about what I just worked on," on scale of 1 (strongly disagree) to 4 (strongly agree). The final curiosity score is the mean response on all eight items. Internal consistency of the curiosity measure was good (Cronbach's alpha day 1 = .85; day 2 = .88).

Affect

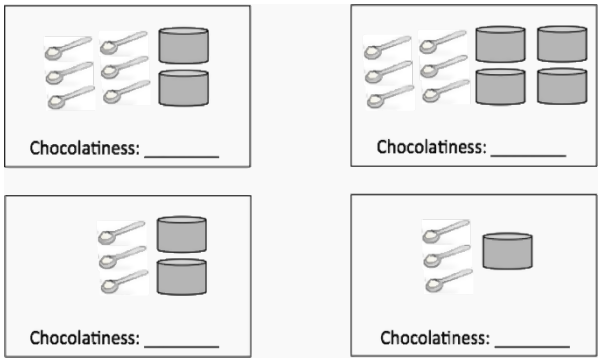
The affect measure was adapted from Laurent et al.'s (1999) PANAS-C scale. The measure includes 12 words that describe affective states – 6 positive (e.g. determined, enthusiastic) and 6 negative (e.g. upset, distressed). Students indicated how much they felt each feeling on a scale of 1 (not at all) to 5 (extremely). Responses for each subscale were averaged to create separate scores for positive and negative affect. Internal consistency was satisfactory. Cronbach's alpha ranged from .72 to .86 across subscales and days.

Learning Pretest and Posttest

The learning pretest/posttest included 4 questions, assessing procedural and conceptual understanding of Hooke's Law and Newton's Second Law formulas (Table 2). It also included two distractor items unrelated to the target concepts, which required students to subtract or multiply, rather than divide, to ward off demand characteristics. There were two isomorphic versions of this test, which were counterbalanced.

Two researchers coded 25% of the data and achieved strong reliability (kappa = .91). Each researcher then coded half the remaining data. Internal consistency was satisfactory ($alpha_{pre}$ = .84, $alpha_{post}$ = .58), given the small number of diverse items that varied in content (Hooke's and Newton's laws) and knowledge type (procedural and conceptual). Similar studies have also reported comparable alpha levels to be acceptable. For example, Loibl and Rummel (2014) consider an alpha of .49 to be satisfactory given the low number of test items. All items were converted to a 0-1 scale, and averaged to compute pretest and posttest scores.

Table 2. *Sample Learning and Transfer Test Items with Scoring Rubric.*

Learning Item	Transfer Item
A force of 10 Newtons moves a spring with a spring constant of 30 N/cm. How far does the spring move?	Hot chocolate is made by mixing cocoa powder and milk. Each box below shows the ingredients that will go into different batches of hot chocolate. Determine the chocolatiness of each batch of hot chocolate. 

0 points	Responded with something other than what is listed under "1 point" or "2 points"	no correct numerical solutions
1 point	Divided in reverse (e.g. "3")	correct numerical solution for 1 batch
2 points	Correctly solved the problem (e.g. "1/3")	correct numerical solution for 2 batches
3 points		correct numerical solution for 3 batches

Transfer Posttest

The transfer posttest contained 4 questions that assessed whether students could apply and adapt ratio structures for novel contexts, adapted from Schwartz et al. (2011). In two of the transfer items, students applied the formulas they learned in a novel situation (e.g. instead of pulling springs, people are standing on and stretching a trampoline mat in a problem about Hooke's Law). In two transfer items, students applied ratio structures in new domains that were not part of their instruction. For example, in the transfer item in Table 2, students would need to use their knowledge of ratio structures to determine the concentration of each cup of chocolate milk. Two coders scored 25% of transfer data and achieved high reliability (kappa = .89), then coded the rest of the data. Transfer items were scored on a 4-point scale (see Table 2), then scaled from 0-1 and averaged. Internal consistency for the transfer test was good (alpha = .84).

Task Performance

To assess differences in the quality of invented formulas between the UU and EU groups, I assessed the number of invented solutions (e.g. iterations), which is often associated with learning outcomes in Invention tasks (e.g. Kapur, 2014) and whether the students correctly invented the target formula. Scores were averaged across both Invention tasks. Due to a data collection error, performance data from the NU group's activities were not available.

Results

We used ANOVA and regression models throughout the Results section. Significant ANOVA models were followed up with planned contrasts to test for hypothesized group differences and Shaffer's planned post-omnibus modification (Levin, Serlin, & Seaman, 1994).

Preliminary analyses suggested that students' honors status and pretest scores had an effect on learning, transfer, and number of Invention tasks correctly solved, but not curiosity or affect. Therefore, in all analyses related to performance, learning, or transfer, I controlled for honors status and pretest. However, pretest and honors status were not included in the model predicting curiosity or affect. Note that I also tested grade level and class as potential control factors but found that neither explained significant variance for any outcome variables. Statistics reported below focus on the main condition effects, rather than control variables, which were not part of my research questions.

Manipulation Check

Students in the expected and unexpected uncertainty groups felt significantly more uncertain than the NU group (M_{UU} = 3.29, SD_{UU} = 1.24; M_{EU} = 3.00, SD_{EU} = .98; M_{NU} = 2.06, SD_{NU} = 1.42), according to ANOVA results, $F(2,135) = 12.69$, $p < .001$, $\eta_p^2 = .16$. Planned contrasts revealed that students in the NU group reported significantly less uncertainty than the EU and UU groups combined, $p < .001$, while the UU and EU groups responded similarly to each other, $p = .28$.

Curiosity and Affect

Condition differences on curiosity, positive affect, and negative affect (averaged between the two days of intervention) were tested in a single MANOVA model because theories of curiosity often equate curiosity with the affect experienced when curious (e.g. Berlyne, 1950,

1955; Kashdan et al., 2004; Loewenstein, 1994), and these variables correlated with one another. There was an umbrella effect of condition, $F(6,268) = 7.41$, $p < .001$, $\eta_p^2 = .14$. Follow-up individual ANOVAs showed a significant difference among conditions in curiosity, $F(2,138) = 20.46$, $p < .001$, $\eta_p^2 = .23$, and negative affect, $F(2,138) = 4.72$, $p = .01$, $\eta_p^2 = .07$, but not positive affect, $p = .13$. Planned contrasts revealed that those in the NU group reported significantly less curiosity than the EU and UU groups combined, $p < .001$. Additionally, the EU group was significantly less curious than the UU group, $p = .005$ (See Figure 4). Further, those in the UU group reported more negative affect than the NU and EU groups combined, $p = .004$. The EU group's negative affect did not differ from the NU group, $p = .40$ (see Figure 5).

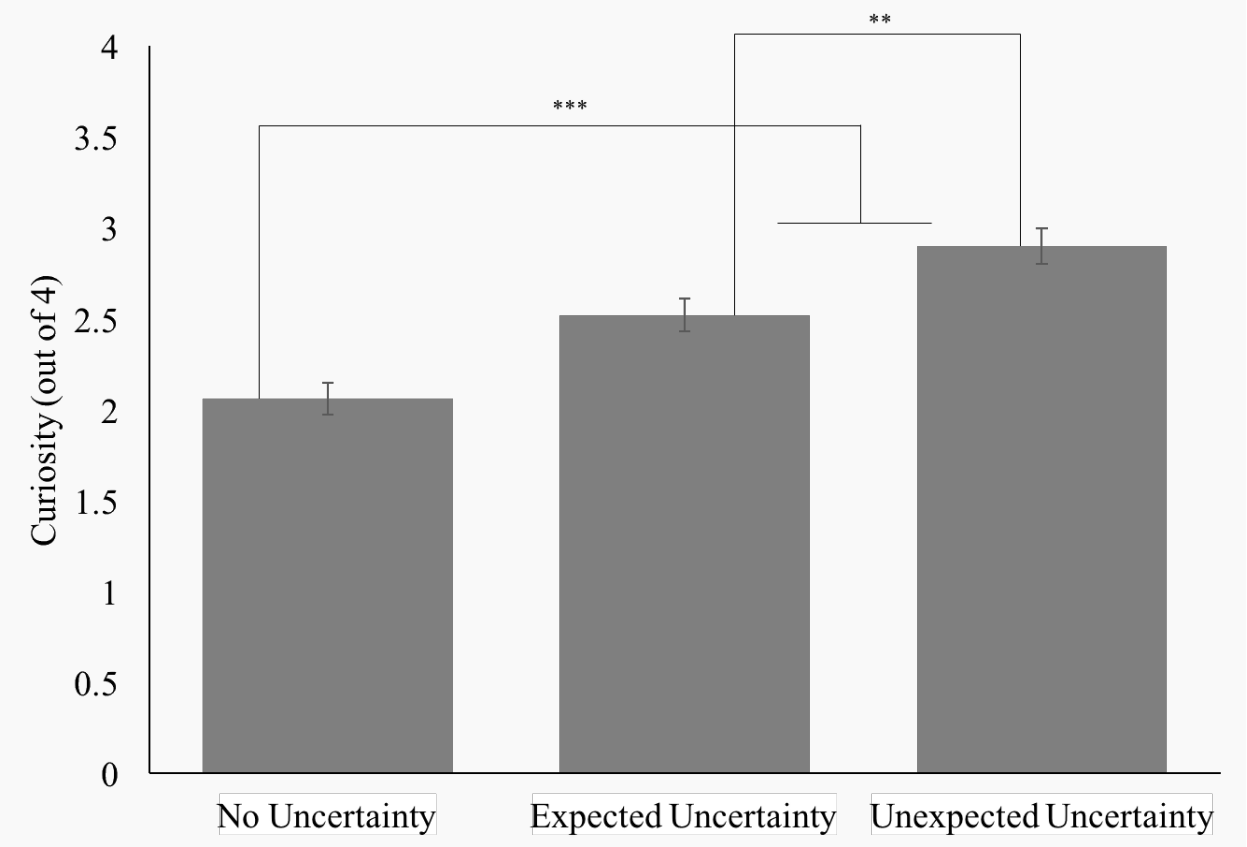


Figure 4. Curiosity Scores. Significant at $^{**}p < .01$, $^{***}p < .001$. Error bars represent ± 1 SE.

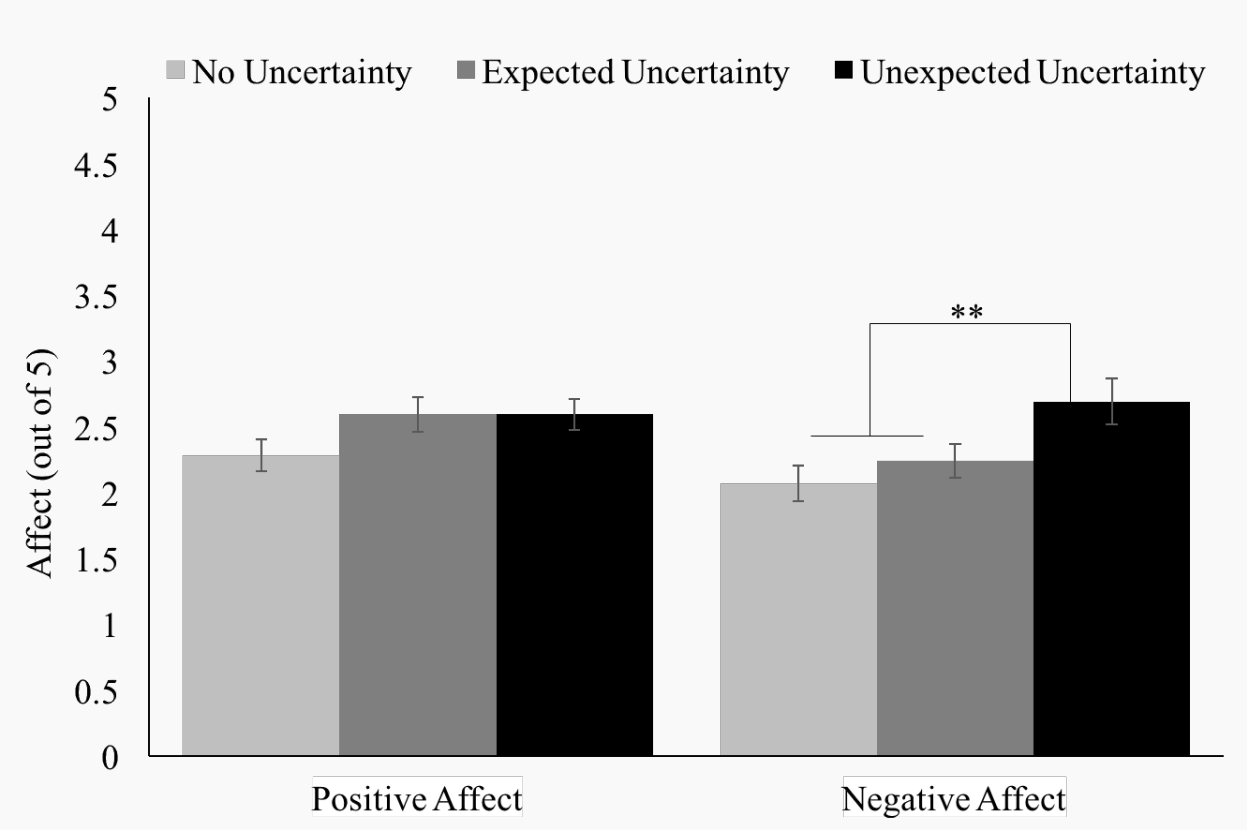


Figure 5. Positive and negative affect. ** Significant at p < .01. Error bars represent ± 1 SE.

To summarize, the uncertainty groups were .65 points more curious than the NU group with a very large effect size, d = .99, and the UU group was .38 points more curious than the EU group, a moderate-sized effect, d = .62. Moreover, the EU manipulation seemed to reduce students' experience of negative affect by .45 points, relative to the UU condition, a small effect, d = .28. All groups reported similar levels of positive affect.

Learning Pretest to Posttest

An initial ANOVA revealed no differences across conditions on pretest scores, $F(2,132) = 1.81$, $p = .17$, indicating that all conditions had similar levels of prior knowledge. Repeated measures ANOVA, controlling for honors status, showed that all conditions learned from pretest to posttest, $F(1,132) = 129.59$, $p < .001$, $\eta_p^2 = .50$, but there were no differences in learning by

condition, $F(2,132) = 0.80$, $p = .92$. However, average pre-post gains across the full sample were 33%, demonstrating sizeable learning, $d = .98$ (see Figure 6).

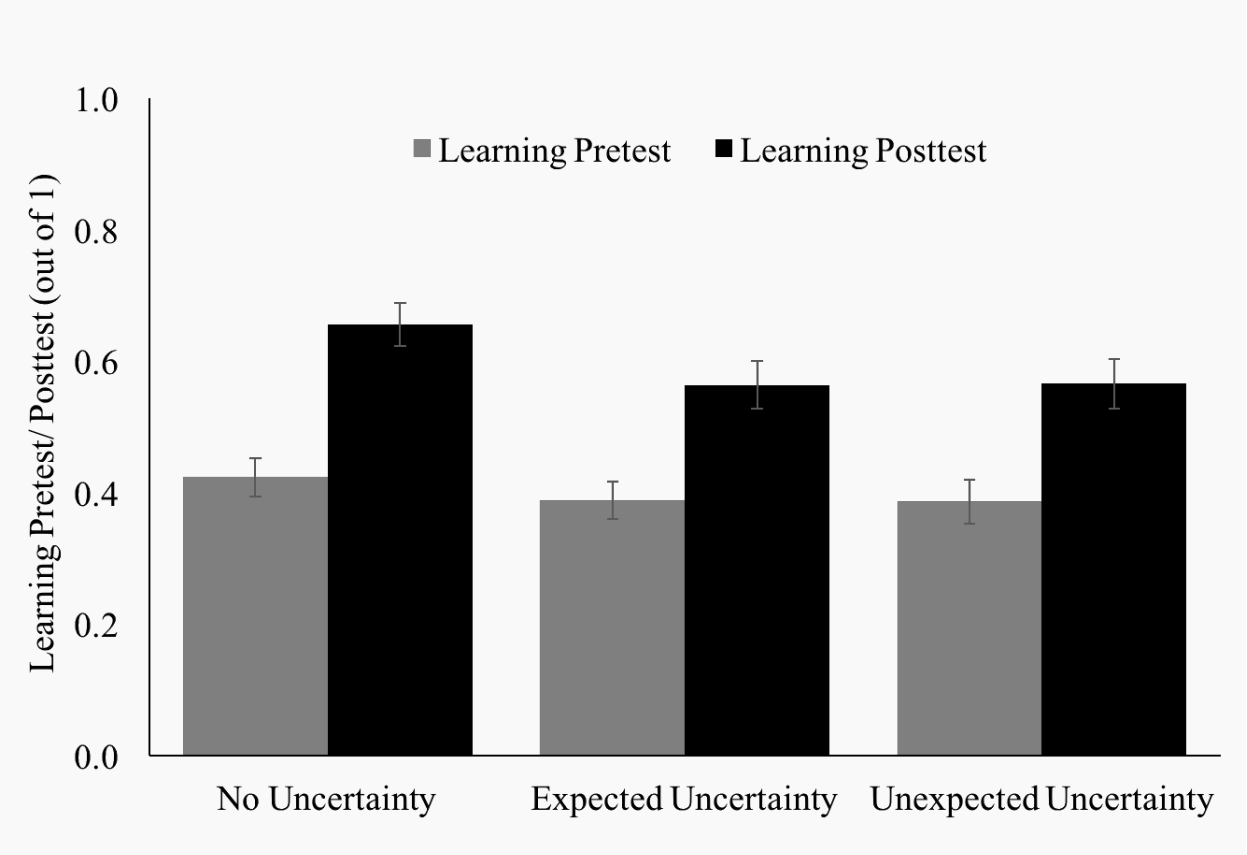


Figure 6. Mean *s*cores on *l*earning *p*retest and *p*osttest. Error bars represent ± 1 SE.

Transfer Posttest

An ANCOVA on transfer test scores, controlling for honors status and pretest score, revealed a significant condition effect, $F(2,131) = 33.97$, $p < .001$, $\eta_p^2 = .34$. Planned contrasts revealed that students in the uncertain groups had significantly higher transfer scores than the NU group, $p < .001$. In fact, the combined transfer score of the EU and UU groups more than tripled the average score of the NU group, with a huge effect size, $d = 1.69$. EU and UU groups performed similarly, $p = .38$ (see Figure 7).

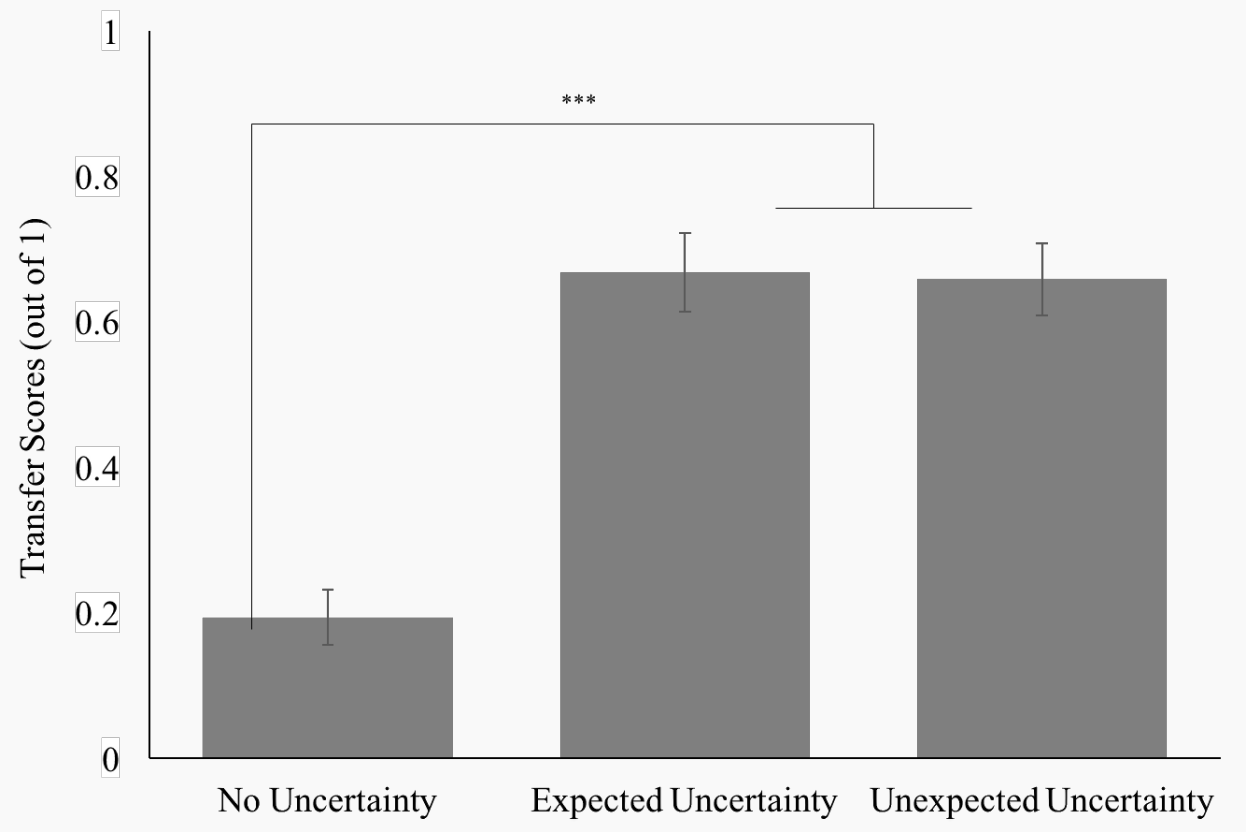


Figure 7. Mean transfer posttest scores. Error bars represent ± 1 SE. *** significant at $p < .001$.

Task Performance

We conducted exploratory analyses to see whether expectations of uncertainty affected task performance. I found that EU and UU groups did not differ in how they performed on the Invention activities, as measured by either the number of invented formulas or the number of correct formulas (Table 3). Note that these analyses include only students who invented (UU and EU), and data was missing from four students, resulting in 85 data points.

Table 3. *Task Performance.*

	Number of Iterations		% of Students		
	M	SD	0 correct	1 correct	2 correct
Expected Uncertainty	2.49	1.07	19%	46%	35%
Unexpected Uncertainty	2.19	.95	17%	39%	44%

An ANOVA, controlling for honors status and pretest score, found no condition differences on the number of iterations students generated during the Invention tasks, $F(1, 80) = 2.62$, $p = .12$. Further, an ordinal regression predicting how many times students successfully invented the target formula (0, 1, or 2), controlling for honors status and pretest score, did not find a significant condition effect, $B = 0.16$, $Wald = 0.15$, $p = .70$. Based on these results, the fact that the UU and EU groups performed similarly to each other at posttest is not surprising.

Predictors of Learning

The more positive affect students felt, the more they learned. However, negative affect and curiosity did not predict learning. To examine predictors of learning, I conducted three linear regressions, in a hierarchical fashion (Table 4). In Model 1, I regressed learning posttest on control variables: honors status and pretest score. Both were significant predictors, such that honors students and students with more prior knowledge performed better on the posttest.

In Model 2, curiosity, positive affect, and negative affect were added to the model, but only positive affect predicted learning, such that every one-unit increase in positive affect ratings was associated with a 7% increase in posttest scores.

Model 3 added dummy variables for condition, which did not explain additional variance, but positive affect remained a significant predictor. I also explored interaction effects and found

no significant interactions between condition and positive affect, negative affect, or curiosity, *p*'s > 12. Results suggest that positive affect predicts learning, regardless of condition.

Table 4. *Regression models predicting learning posttest*

	B	*SE B*	*β*	*F* (df)	Δ*F* (df)	R^2	ΔR^2
Model 1				17.36(2,135)**	-	.2	-
Honors*	.08	.04	.17				
Pretest***	.39	.09	.37				
Model 2				10.434(5,132)*	4.83(3,132)**	.2	.07
Honors	.07	.04	.14				
Pretest***	.34	.09	.32				
Curiosity	-.03	.03	-.09				
Positive Affect**	.07	.03	.28				
Negative Affect	-.02	.02	-.11				
Model 3				7.463(7,130)**	.31(2,130)	.2	.00
Honors	.06	.04	-.08				
Pretest***	.34	.09	.31				
Curiosity	-.03	.03	-.08				
Positive Affect**	.07	.03	.28				
Negative Affect	-.02	.02	-.11				
EU Condition	-.03	.04	-.07				
UU Condition	-.01	.05	-.02				

Significant at *$p < .05$, **$p < .01$, ***$p < .001$.

Predictors of Transfer

For transfer, I found a different pattern: curiosity predicted transfer, but affect did not. However, once variables for condition were added to the model, curiosity was no longer a

significant predictor. To examine predictors of transfer, I conducted the same three regressions used to predict learning, but with transfer scores as the outcome variable (Table 5). Model 2 shows that curiosity was positively related to transfer, such that every one-unit increase in curiosity ratings was associated with a 15% increase in transfer scores. Positive and negative affect did not significantly predict transfer. However, once dummy variables for condition were added in Model 3, curiosity was no longer a significant predictor, and the percent variance explained increased by 27%. This suggests that condition explains all the variance in transfer scores related to curiosity, and more. This makes sense, given that conditions differ in both curiosity and transfer test performance. Note that I did test for interactions between condition and the three affect variables (curiosity, positive affect, negative affect) and found none, *p*'s > .06.

One interpretation of these results is that the relationship between curiosity and transfer is spurious and is solely explained by two independent relationships – one between condition and transfer and the other between condition and curiosity. Another interpretation is that condition is influencing transfer performance through two pathways – by directly enhancing transfer and by indirectly enhancing curiosity, which, in turn, enhances transfer. Unfortunately, I did not have a large enough sample size to analyze for mediation effects (Fritz & MacKinnon, 2007).

Table 5. *Regression Models Predicting Transfer*

	B	*SE B*	*β*	*F* (df)	Δ*F* (df)	R^2	ΔR^2
Model 1				6.34(2,135)**	-	.0	-
Honors**	.30	.07	.27				
Pretest	.10	.17	.05				
Model 2				5.09(5,132)***	3.98(3,132)**	.1	.08
Honors*	.18	.07	.22				

Pretest	.12	.17	.07				
Curiosity*	.15	.06	.28				
Positive Affect	.003	.05	.006				
Negative Affect	-.005	.03	-.01				
Model 3				13.85(7,130)***	30.12(2,130)*	.4	.27
Honors**	.18	.06	.22				
Pretest	.20	.14	.10				
Curiosity	.01	.05	.02				
Positive Affect	.02	.04	.05				
Negative Affect	-.02	.03	-.05				
EU Condition***	.48	.07	.59				
UU Condition***	.44	.08	.53				

Significant at *$p < .05$, **$p < .01$, ***$p < .001$.

Discussion

In my first hypothesis, I predicted that the EU and UU groups would become more curious than the NU group, but would not differ from one another. This hypothesis was partially confirmed. As predicted, the EU and UU groups reported greater curiosity than the NU group. However, I was surprised to find that giving expectations about uncertainty led to lower curiosity than not giving expectations. Perhaps this is because giving expectations about uncertainty, in a way, reduced uncertainty, by giving students information about the problem-solving *process*, even though students did not receive additional information about content.

In line with my second hypothesis, I found that giving student expectations of uncertainty buffered the effects of uncertainty on negative affect. That is, when students expected the uncertainty, they reported lower negative affect compared to students who were not given such expectations but were put in an uncertain situation. Additionally, the negative affect of students

with expected uncertainty did not differ from students who experienced no uncertainty. However, the level of reported positive affect did not differ across conditions.

Our third hypothesis predicted that students in the EU and UU groups would learn and transfer more than students in the NU groups and that students who were given expectations of uncertainty (EU) would learn and transfer more than students who were not given expectations of uncertainty (UU). My data partially support this hypothesis. On transfer outcomes, I found that as predicted, the EU and UU groups transferred more than the NU group. However, contrary to my predictions, the EU and UU conditions performed equally well. This could be because the effect that uncertainty had on curiosity overshadowed the effect it had on negative affect, thus not resulting in significant differences in transfer between the two groups. This is supported by my data which show that curiosity, and not affect, predicted transfer.

Additionally, my data did not show evidence of differences in learning among the three groups. This is surprising because a lot of theory and research suggest that instruction that makes students more curious results in greater learning (e.g. Gruber et al., 2014; Lamnina & Chase, 2017). One possible explanation for this unexpected result is that my learning posttest was relatively simple and thus, my measures reflect fairly basic, rather than deep learning. It may be that curiosity is more important for deep learning or challenging test situations, such as transfer (National Research Council, 2012). Likewise, transfer items often detect differences in learning experiences that simple learning items might miss (Bransford et al., 2000). Alternatively, it may be that my measure of learning was imperfect and therefore could not capture condition differences. Internal consistency of the learning posttest was relatively low. While I believe the internal consistency is acceptable because of the low number of questions that tested

heterogeneous constructs (Tavakol & Dennik, 2011), the learning results should be taken with caution (see discussion of my learning measure in the Limitations and Future Directions section).

The above explanations are supported by the finding that curiosity predicted only transfer, not learning, in partial support of my fourth hypothesis. However, it should be noted that compared to curiosity, condition was more predictive of transfer. This means that while curiosity predicted transfer, it is unclear if this was causal, or an artifact of the fact that curiosity was collinear with condition. In other words, condition might have influenced curiosity and transfer, but the two outcomes might not be related to one another. Another possibility is that condition influenced curiosity, which, in turn, influenced transfer, but other condition effects influenced transfer, as well. For example, Invention may have partially influenced transfer through cognitive mechanisms, which is supported by prior research (Loibl et al., 2017).

Finally, in my fifth hypothesis, I predicted that positive affect would positively predict learning and transfer, while negative affect would negatively predict learning and transfer. In line with this prediction, I found that positive affect positively predicted learning. However, negative affect did not predict learning and neither positive nor negative predicted transfer. This could be because positive affect influenced direct learning by leading students to engage in the activities more or by increasing their desire to learn (Kashdan et al., 2004), but when it came to deeper learning required for transfer, affect did not matter as much. Additionally, while negative affect might have increased task-irrelevant thoughts (Howell & Conway, 1992; Seibert & Ellis, 1991) or slowed down students' rate of skill acquisition (Greene et al., 1998), this might not have been enough to have a negative effect on learning and transfer in my particular learning activities.

Implications

Taken together, these findings contribute to practice, instructional design, and educational psychology literature. First, while prior research has examined the connection between uncertainty and curiosity and between curiosity and learning, to my knowledge, little work has explored this connection in classroom settings where content learning is considered. The present work addresses this gap and provides support for the use of inherently uncertain instruction, such as Invention, in the classroom, suggesting that if educators induce some level of uncertainty in their lessons rather than simply providing facts, they can create an environment that begets motivated, curious learners. More broadly, this work suggests that open-ended and exploratory learning activities, such as discovery or problem-based learning, which are inherently uncertain, may raise learners' curiosity, while facilitating the development of transferable knowledge. Moreover, this work contributes to the literature on Invention and productive failure, which previously considered use of prior knowledge, noticing of deep features, and awareness of knowledge gaps as mechanisms for the effectiveness of Invention (Kapur, 2008; Loibl et al., 2017; Schwartz et al., 2011), but has largely overlooked uncertainty and curiosity, which may result from awareness of knowledge gaps (Loewenstein, 1994).

Additionally, this research contributes to literature on transfer of learning. While there is a large body of research uncovering ways to facilitate transfer (e.g. Kapur & Bielaczyc, 2012; Loibl et al., 2017; VanLehn, Siler, Murray, Yamauchi, & Baggett, 2003), such work does not consider non-cognitive variables, such as curiosity. Yet, in this study, curiosity was positively associated with transfer. While more work is needed to elucidate this relationship by teasing apart effects of condition and effects of curiosity on transfer, this research serves as a promising addition to the small body of work on non-cognitive variables that influence transfer (e.g.

Belenky & Nokes-Malach, 2012; Pugh & Bergin, 2006). Furthermore, my data show that by using an uncertain form of instruction, educators can teach their students in a way that allows them to carry their knowledge beyond the original learning context and transfer it to novel contexts. To my knowledge, research on uncertainty has not taken transfer into account and has focused almost exclusively on direct learning.

Further, the present study adds to research on uncertainty by comparing expected vs. unexpected uncertainty in a real-world setting. I show that students who watched a simple, 26-second video that told them that they should expect to feel uncertain during the lesson, reported a similar level of negative affect as those who experienced no uncertainty. This simple solution could offset concerns that educators might have about using uncertain instruction in their classrooms. However, giving expectations also resulted in less curiosity than not giving expectations. Nevertheless, the difference in curiosity between the EU and UU groups did not seem to matter a great deal since the two groups did not differ in learning or transfer.

Limitations and Future Directions

While I found some promising results in this research, this study had some limitations and revealed additional questions for future research to address. First, because there were differences other than uncertainty between conditions, I cannot fully conclude that uncertainty is what caused the differences in curiosity or transfer outcomes. Specifically, students who completed the Invention activity were more actively involved in the learning because they had to generate their own ideas, compared to students who listened to the lecture and the completed practice problems, who could more passively plug numbers into a formula. These differences in level of active involvement could have also caused differences in transfer between conditions. However, it should be noted that the manipulation checks did show that those who invented, did,

in fact, feel more uncertain. To confirm that it is, in fact, uncertainty influencing curiosity and transfer, future work should examine learning activities that are more similar to one another, but still differ in uncertainty. For example, a study could compare two Invention conditions, in which one group of students is given more information than the other.

Second, because of the nature of comparing conditions in which the order of direct instruction and practice is reversed, students in the groups that invented saw the direct instruction closer in time to the posttest. This could have influenced how well they did on the test in comparison to their peers. This is especially true of the ratio video, which the EU and UU groups saw a full day after their peers who received direct instruction first. One way to reduce the possibility of this effect is to include a longer delay between the end of instruction and the posttest.

Another limitation in comparing such conditions is that the timing of the curiosity measure differs between groups. Because the NU and EU conditions had no measure of curiosity once the full instruction had been implemented, I do not know if they were still curious once they heard the lecture. Moreover, because there was no pre-measure of curiosity for the No Uncertainty condition, I do not know how curious they were to watch the videos. To address this, future work should measure curiosity for all groups before and after they are given content information.

Finally, because of the relatively low level of internal consistency of my learning posttest measure, I am limited in the conclusions I could draw about learning outcomes. However, low internal consistency could be justified in the case of my test because of the high variety of question types and low number of questions (Tavakol & Dannik, 2011). Nonetheless, it is

unclear if my measure was reliable. Because of this, I cannot say for sure that my learning results are accurate.

Future studies could also explore curiosity and uncertainty in the context of other inherently uncertain forms of instruction, such as productive failure (e.g. Kapur, 2008), predict-observe-explain protocols (e.g. Smith, Edionwe, & Michel, 2010), or discovery learning. Researchers may find that these methods may impact transfer by raising learners' uncertainty, which, in turn, influences their curiosity. Moreover, because Invention activities have been shown to aid in awareness of knowledge gaps (Loibl et al., 2017), future work, in line with the information-gap model of curiosity (Loewenstein, 1994), could test whether this is the reason why students who invent experience more curiosity. Finally, future studies can examine if my results hold true when accounting for individual differences. For example, intolerance of uncertainty is a characteristic that reflects generally negative beliefs about uncertainty and is associated with negative reactions to uncertainty on emotional, cognitive, and behavioral levels (Buhr & Dugas, 2009). Thus, future work could explore whether individual differences in intolerance of uncertainty would lead to different reactions to my intervention, in terms of affect, curiosity, learning, and transfer.

Conclusion

We compared inherently uncertain instruction (with or without expectations) to inherently certain instruction. Overall, this study demonstrates the value of uncertainty in science instruction. It also shows one practical way that uncertainty can be created: by asking students to invent their own formulas first, before receiving content information. I demonstrate that doing so leads students to feel more curious about what they are learning and enables them to better transfer their knowledge to new contexts. Additionally, I show that this can be accomplished

without causing students to experience the negative affect often associated with uncertainty, by simply telling them about the uncertainty. Because this body of work is fairly new, there is much left to be explored, including uncovering the optimal level of uncertainty and finding other ways of making instruction uncertain. I hope that this research serves as a jumping off point for other researchers and practitioners who are seeking to design instruction with the goal of enhancing learners' curiosity.

Chapter 3: Uncertain Instruction: Effects on Curiosity, Learning, and Transfer (Paper 2)

Abstract

Theory and research suggest that uncertainty leads to curiosity. In turn, curiosity is associated with learning. However, educational research rarely examines the effect that uncertainty has on curiosity, learning, or transfer, a reflection of deeper learning. Additionally, research on the effect of curiosity on learning rarely considers state-level curiosity or how curiosity changes as learners receive more information. In a study with 208 middle school students learning physics, I addressed these gaps. Two conditions completed learning activities differing in levels of uncertainty. The High Uncertainty (HU) condition received problem-irrelevant information before completing Invention tasks, while the Low Uncertainty (LU) condition received problem-relevant information before completing the same Invention tasks. Both groups learned the content equally well, but the HU condition both demonstrated and reported greater state-level curiosity and performed better on transfer problems than the LU condition. I show that curiosity decreases over time as students gain more information. Surprisingly, curiosity did not predict learning or transfer. This contributes to the literature by examining uncertainty in the context of a real-world classroom and measuring self-reported and behavioral state-level curiosity. This study also demonstrates a practical approach for educators to induce uncertainty to increase students' curiosity and transfer.

Keywords: uncertainty, curiosity, learning, transfer, Invention

Uncertainty, defined as a lack of information or predictability in an environment (e.g. Mushtaq, Bland, & Schaefer, 2011), has been shown to be a key variable for fostering curiosity (Edleman, 1997), which is thought to be a prerequisite for knowledge construction (Piaget, 1952). Therefore, it goes to reason that inducing some level of uncertainty into lessons could lead to both increased curiosity and increased learning and transfer. Previous research, did, in fact, find that uncertainty increased curiosity (Lamnina & Chase, 2017; Lamnina & Chase, in press). Additionally, pedagogies, such as invention and productive failure activities, which are inherently uncertain, have been successful in increasing learning transfer, especially in STEM (e.g. Schwartz & Bransford, 1998; Shemwell, Chase, & Schwartz, 2015). Thus, it is reasonable to predict that instruction high in uncertainty, where information is not immediately apparent, would lead to greater curiosity and learning compared to instruction low in uncertainty, where information is immediately apparent. In this paper, I describe a classroom study comparing different levels of uncertainty in an exploratory learning activity and investigate how they influence students' curiosity, learning, and transfer of physics and related mathematical concepts.

Uncertainty

Uncertainty is a commonly proposed cause of curiosity in theory and research. It is defined as ambiguity of a task (Alison et al., 2015) or a lack of predictability in an environment (Mushtaq, Bland, & Schaefer, 2011). Curiosity-drive theory explains that people are motivated to seek information that is lacking in order to reduce uncertainty and return to a state of coherence (Berlyne, 1954, Dashiell, 1925; James, 1950). Comparably, in his cognitive disequilibrium theory, Piaget (1952) writes that as children develop, they encounter new information, which make them uncertain, leading them to explore further and encounter more uncertain experiences, This results in a cycle of curiosity and exploration. In his incongruity theory, Hebb (1955) also

that when events do not match one's expectations of what should happen, thereby making them uncertain, their sense-making desire is triggered. Similarly, Loewenstein's (1994) knowledge-gap theory explains that when individuals become aware of their uncertainty, they desire information to fill their knowledge gap (Golman & Loewenstein, 2018). Despite differences in how these theories describe curiosity (i.e. as a drive, a part of development, an innate desire) they all focus on the role that uncertainty plays. Applying them to curiosity in the classroom leads us to predict that some uncertainty in instruction should be beneficial for increasing curiosity.

Empirical research substantiates the link between uncertainty and curiosity. For example, studies in which teachers or researchers drew students' attention to uncertainty have demonstrated increases in students' curiosity (e.g. Fisher, HirshPasek, Newcombe, & Golinkoff, 2013; Markey & Loewenstein, 2014; Weisberg, Hirsh-Pasek, Golinkoff, Kittredge, & Klahr., 2016). Additionally, studies in which uncertainty was increased by decreasing how obvious a correct choice was, increasing the number of possible options, or making outcomes unknown have all resulted in increased curiosity (e.g. Berlyne, 1962; Boykin & Harackiewicz, 1981; Hsee & Ruan, 2016). Similarly, increasing uncertainty by showing outcomes of events contradictory to one's expectations led to increased curiosity, both self-reported and behavioral (e.g. Campion et al., 2009; Stahl & Feigenson, 2015). Other studies have shown that in problem-based learning processes, curiosity decreases as uncertainty is reduced, with students showing the most curiosity when the problem is initially presented, less curiosity after having spent some time working on the problem, and even less curiosity after elaboration of what was learned (e.g. Rotgans & Schmidt, 2011; Tripathi et al., 2015). Finally, research induced uncertainty by withholding information about content (e.g. Campion et al. 2009; Lamnina & Chase, 2017; Lamnina & Chase, in press; Loibl & Rummel, 2014; Rogtans & Schmidt, 2014) or process (e.g. Cyr, 1996;

Loibl & Rummel, 2014) has also resulted in higher curiosity. Together, these studies show that uncertainty can be induced in a variety of ways across diverse content, settings, and participants, and lead to increased curiosity.

A simple way to induce uncertainty is to withhold information. Withholding information about content (e.g. Campion et al. 2009; Lamnina & Chase, 2017; Lamnina & Chase, in press; Loibl & Rummel, 2014; Rogtans & Schmidt, 2014) or process (e.g. Cyr, 1996; Loibl & Rummel, 2014) have also resulted in higher curiosity. For example, Lamnina and Chase (in press) manipulated uncertainty by withholding problem-relevant information. They gave a group of students direct instruction about science concepts followed by problem-solving activities and compared this condition to a group who completed analogous activities before receiving direct instruction. While the problem-solving activities completed by both groups were comparable, problem-solving before direct instruction was more uncertain because students lacked information about how to solve the problems. This group reported higher curiosity than the group that received the certain, direct instruction right away. Similarly, Rogtans and Schmidt (2014) asked middle school students why the British and Allied Forces lost a battle in World War II, despite outnumbering their opposition. One group of students read information that could help them solve the problem, while another group read irrelevant text. Students who read the irrelevant text, and thus experienced more uncertainty about the problem, reported higher curiosity. In this study, I manipulate uncertainty by withholding information, similar to Rogtans & Schmidt (2014).

Despite considerable research linking uncertainty with curiosity, this review illustrates several gaps and limitations. For example, most of this research was conducted in well-controlled lab studies, which do not necessarily reflect what would happen in a real classroom.

Additionally, this research tended to gauge curiosity via self-report measures, which can be inaccurate due to consistency-seeking behaviors, self-enhancement tendencies (Sedikides & Strube, 1995), or a lack of self-knowledge, (Dunning, Heath, & Suls, 2004), or through behavioral measures that are conflated with social factors. For example, Smith, Johnson, and Johnson (1981) and Lowry and Johnson (1981) measured curiosity by frequency of use of an "information station" or frequency of attendance to an optional film during recess. While both of these are behavioral measures that examine information-seeking behaviors, they are limited in that they are conflated with social factors. For example, children's choices in classroom settings are often heavily influence by their peers' choices. Thus, there is a need for behavioral measures of curiosity that can be validly assessed in classroom settings.

Moreover, the focus of this literature tended to be on straightforward, well-structured tasks, such as selecting an answer choice, pressing a button, or reading a story, rather than on exploratory problems with unclear goals or insufficient information to solve them (Sinnott, 1989; Voss & Post, 1988). This needs to be addressed because this kind of instruction (i.e. inquiry, discovery, or exploratory problem solving) is growing in popularity (e.g. Barrett & Moore, 2010; Hung & Loyens, 2012; Schwartz, Mennin, & Webb, 2001). Yet, only one case study (e.g. Cyr, 1996) and three experimental studies (e.g. Loibl & Rummel, 2014; Lamnina & Chase, 2017; Lamnina & Chase, in press) have examined the relationship between uncertainty and curiosity in less-structured, inherently uncertain instruction. In addition, these studies had limitations. For example, Loibl and Rummel (2014) and Lamnina and Chase (in press) both compared an inherently uncertain form of instruction, in which students had to first invent a solution and then receive direct instruction, to an inherently certain form of instruction, in which students received all the information about the target content immediately and then completed practice problems.

However, in this manipulation there are differences other than uncertainty between conditions, so I cannot fully conclude that uncertainty is what caused the differences in curiosity. Specifically, students who invented were more actively involved in the tasks because they had to generate their own ideas, compared to students who listened to the lecture and then completed practice problems. This could have led the Invention groups to feel more curious than the other group, independent of uncertainty. Thus, cleaner comparisons of varying levels of uncertainty within the same form of exploratory instruction are needed.

Additionally, while the described theories and studies explored how uncertainty influenced curiosity, most did not consider how curiosity is related to learning and transfer. Further, almost all these studies focused on curiosity as a trait, rather than a state that can be more easily influenced (Grossnickle, 2016), perhaps with instruction. Finally, only two of these studies considered how curiosity changes over the course of a lesson (e.g. Rotgans & Schmidt, 2011; Tripathi, 2015).

Curiosity

Curiosity can manifest in many ways, such as sensory/perceptual curiosity, physical curiosity, social curiosity, or intellectual/cognitive curiosity, all of which can occur either as individual traits or temporary states (Grossnickle, 2016). In this paper, I focus on cognitive curiosity, which is the desire for new information (Berlyne, 1954; Berlyne, 1966; Tripathi et al., 2015). For instance, a cognitively curious student may read additional books about the topic he learned in school that week if he felt as if he was lacking sufficient information on the topic. Cognitive curiosity seems to have the most direct implications for content learning, and will thus, be the focus of this study. Additionally, because I am interested in eliciting curiosity for specific

content information as it is being taught, I will be analyzing curiosity as a state, rather than a trait.

Cognitive curiosity is different from, though related to, interest, "a psychological state of attention and affect toward a particular object or topic, and an enduring predisposition to reengage over time" (Harackiewicz et al., 2016, p. 1). Specifically, they differ in the goals that drive them: interest is driven by the goal of pursuing enjoyment, while curiosity is driven by the goal of filling a specific knowledge gap (Grossnickle, 2016; Renninger & Hidi, 2016).

Curiosity's Relationship to Learning

Learning is particularly important to consider when studying curiosity in classroom settings, because theory and research suggest that curiosity aids in learning. For example, Erikson (1950) theorized that young people who are curious about possible social roles will learn more about what roles best suit their interests and abilities. Similarly, Voss and Keller (1983) posited that those who are more inclined to be curious about their environments, explore them more, and therefore, learn more about them. Finally, Reio et al. (2006) suggested that curiosity leads individuals to seek information, which promotes knowledge construction.

Much empirical research, mainly focusing on curiosity as a trait, supports these theories. For example, a meta-analysis of characteristics affecting academic achievement revealed that curiosity predicted academic performance (von Stumm et al., 2011). Parent and teacher ratings of children's curiosity also predicted achievement (Shah et al., 2018) and standardized test performance (Alberti & Witryol, 1994). Additionally, curiosity has been shown to result in greater recall, persistence, and reading comprehension (Arnone et al., 1994; Ainley et al., 2002). Put together, this research points to trait-level curiosity as a key factor for learning and academic success.

However, there is less research examining whether state-level curiosity predicts learning. Research with community college students learning physics, showed that state-level curiosity predicted learning (Lamnina & Chase, 2017). Gruber et al. (2014) showed that adult participants were more likely to learn answers to trivia questions that made them more curious. Other research, outside of the classroom, showed that in aging populations state-level curiosity predicted exploration (Vogl, Pekrun, Murayama, & Loderer, 2019), contributed to cognitive function (Sakaki, Yagi, & Murayama, 2018), and predicted judgements of learning, which should be beneficial for memory (McGillivray, Murayama, & Castel, 2015).

Taken together, this literature suggests that curiosity facilitates learning and academic achievement. Nevertheless, very few studies have considered uncertainty, curiosity, and learning together. Additionally, there is a scarcity of research on state-level curiosity. This gap needs to be addressed, especially since state-level curiosity may be more easily influenced than a stable personality trait. Finally, while prior research aimed to examine the effect of curiosity on academic achievement and performance, recall, and learning, fewer studies examine the connection between curiosity and transfer.

Curiosity's Relationship to Transfer

Transfer is the ability to apply knowledge to a different context than the one in which it was learned (Klahr & Chen, 2011). This is a key goal of education, since schooling should prepare students for life outside of school, which requires them to apply what they learned in school to new contexts. However, transfer is rare (Detterman, 1993; Gick & Holyoak, 1983) and tends to occur only when students learn the content deeply (Bransford et al., 2000). Given that the literature suggests that curiosity should enhance learning, it is reasonable to predict that it will also increase transfer. Yet, only two studies have examined the connection between curiosity

and transfer of what was learned (Lamnina & Chase, 2017; Lamnina & Chase, in press), and those results were inconclusive. Thus, more research testing whether and how curiosity affects transfer is needed.

The Present Study

In the current study, I examine different levels of uncertainty within the same learning activity. Both conditions in my study complete an Invention problem-solving task in which learners invent equations for scientific phenomena (Schwartz & Martin, 2004). I manipulated uncertainty by providing one group with information that about problem-solving process (Low Uncertainty Group) and providing irrelevant information to the other group (High Uncertainty Group), as done by Rogtans and Schmidt (2014) in a study exploring curiosity in a history class. This study is a follow-up to Lamnina and Chase (in press), which compared two groups that invented (high uncertainty conditions) to a group that received direct instruction prior to problem-solving (low uncertainty condition). By having both groups invent in the current study, I ruled out differences in curiosity due to differences in type of instruction. I also eliminated other limitations of comparing tell-then-practice to Invention conditions, such as differences in time between instruction and posttest and differences in timing of the curiosity measure. I compared state-level curiosity between these conditions, both via self-report and behaviorally, and tested how curiosity changed over time.

Further, I tested whether curiosity predicted learning and transfer. Prior research showed that Invention activities followed by direct instruction resulted in greater transfer than direct instruction followed by problem-solving practice (e.g. Schwartz et al., 2011). I suspect that one reason for this is that Invention activities are more uncertain, which increases learners' curiosity. If this is, in fact, one reason for the increased learning and transfer, then a higher uncertainty

Invention activity should also result in greater learning and transfer than a lower uncertainty Invention activity.

In the current study, two conditions were challenged to invent formulas for physical science concepts, while working with a computerized simulation. This activity was more uncertain for one group (High Uncertainty) because students were given no prior information or direct instruction for how to "invent a formula." Thus, the task was ambiguous and the correctness of their formula was unpredictable. The other group (Low Uncertainty) experienced less uncertainty because they received some initial information about what a formula is, what their final answer should look like, and how to invent the formula. After Invention, both groups viewed a short lecture on the relevant formulas and concepts.

Based on my review of the literature I developed the following hypotheses:

(1) Before direct instruction, students in the High Uncertainty (HU) condition will become more curious than those in the Low Uncertainty (LU) condition. Overall, curiosity will decrease throughout the lessons as students receive more information.

(2) Given my prediction about greater curiosity in the HU condition, students working in the HU condition will learn and transfer more than students working in the LU condition.

(3) Regardless of condition, students' levels of curiosity will positively predict how much they learn and transfer.

Method

Participants

Seventh- and eighth-grade students (N = 208) from ten classes in a public middle school in New Jersey participated in this study during their regular 50-minute science classes. The

school's student population was 54% male and 96% Hispanic, and 95% of students were eligible for free or reduced-price lunch. Twenty-eight percent of students were Honors students.

Instructional Content

The instruction focused on two physics concepts: Hooke's Law and Newton's Second Law. These concepts are part of Next Generation's Science Standard for grades 6-8 (NGSS, 2013). Hooke's Law (displacement = force/ spring constant) and Newton's Second Law (acceleration= force/mass) both follow a ratio structure. This structure is common in middle school physical science equations, and many physics concepts cannot be understood without an understanding of ratio (Bailey et al., 2014). Thus, another goal of my instruction, arguably the most important for transfer, was to have students understand ratio structure, allowing them to apply this knowledge to novel formulas.

Procedure

Students within each class were randomly assigned to one of two conditions: High Uncertainty (HU, n = 111) and Low Uncertainty (LU, n = 97), so that each class contained both conditions. The study took place over a total of five class periods (Table 6). First, students took a learning pretest. One to two weeks later, they worked independently on learning activities and surveys for two days. During these two instruction days, the general sequence was modeled after other studies of Invention (e.g. Chase & Klahr, 2017; Schwartz et al., 2011) and the timing of the curiosity survey was modeled after studies that examine how curiosity changes over a problem-based learning process (e.g. Rotgans & Schmidt, 2011; Tripathi et al., 2015; see Table 6). On the following day, students received direct instruction. Finally, one day later, they took learning and transfer posttests and a final curiosity survey. The only difference between groups were the instructions given in the Uncertainty Manipulation Video, with the LU group receiving more

information to help them solve the problem. All sessions were led by the same experimenter, along with one to three research assistants who helped monitor the classroom.

Table 6. *Study Design and Timing*

Pretest	Day 1: Hooke's Law Activities	Day 2: Newton's Second Law Activities	Day 3: Direct Instruction	Posttest
Learning Pretest (20 mins)	Uncertainty Manipulation Video (2.5 mins)*	Uncertainty Manipulation Video (2.5 mins)*	Direct Instruction (10-30 mins)	Learning Posttest (20 mins)
	Uncertainty Survey (2 mins)	Uncertainty Survey (2 mins)	Curiosity Survey (2 mins)	Transfer Posttest (20 mins)
	Curiosity Survey (2 mins)	Curiosity Survey (2 mins)		
	Invention Activities (25-30 mins)	Invention Activities (25-30 mins)		
	Curiosity Survey	Curiosity Survey		

(2 mins)	(2 mins)
Curiosity Worksheet (5 mins)	Curiosity Worksheet (5 mins)

* Differs by condition.

Materials

Uncertainty manipulation videos.

To manipulate uncertainty between groups while still having all students complete invention activities, I manipulated the instructions students received prior to invention on each day. To reduce uncertainty, the LU group received relevant information about their final goal and the process to get there. For example, they were given information about what a formula is, along with example formulas. However, they did not receive content information that would give away the answer or undermine the inventive nature of the task. Differently, the HU group received irrelevant information about the definition and history of science. To increase uncertainty, the goal in this instance was to not give students any information about what they were to do, but to control for timing between conditions and ensure that the procedure was as similar between conditions as possible. Table 7 shows excerpts of the transcripts of videos shown to both conditions.

Table 7. *Quotes from Instructions Given Before Invention on Each Day*

LU Condition	HU Condition
"… you will be creating a formula to connect three variables using math. That means you	"The word science comes from the Latin word for 'knowledge.'"

should be adding, dividing, multiplying, or subtracting. Your formula should also include an equals sign."	
"For example, the formula for the volume of a box is V = l × w × h."	"After the fall of the Western Roman Empire, Greek ideas of the world were preserved in the Muslim world during the Islamic Golden Age."
"…when l=10, w=5 and h=4, then V = 10 × 5 × 4 = 200."	"Modern science is typically divided into three major branches: the natural science, like biology, chemistry, and physics..."
"… come up with a formula to describe how far a spring moves. Your formula must work for all scenarios where a spring is being pushed or pulled."	"… come up with a formula to describe how far a spring moves. Your formula must work for all scenarios where a spring is being pushed or pulled."

Invention activities.

All participants completed two activities, detailed in Lamnina and Chase (in press) about Hooke's Law on Day 1 and about Newton's Second Law on Day 2. In the first activity they invented formulas using contrasting cases and tested their invented formulas by plugging in

numbers from the contrasting cases examples. Once they successfully invented a formula that worked for all four examples, or after 30 minutes had passed, they moved on to the next activity.

In the second activity, students complete thee problems in which they tested their formulas using computerized simulations to further evaluate their invented solutions and focus on the formula's ratio structure. They were to set up the simulations to show two different ways of producing the same outcome and check whether the simulated numbers matched those calculated using the formula they invented.

Direct instruction.

Invention is meant to serve as preparation for future learning (Schwartz & Martin, 2004). Thus, after they completed the activities, students received direct instruction in the form of reading materials and a video. These expository materials described the formulas with real-world examples (e.g. "Have you ever jumped on a bouncy mattress?"), provided the names of the laws and their formulas, defined each variable in the formulas (e.g. "Spring constant is how stretchy or stiff a spring is."), and went through two worked examples. After, students watched a video that explained that ratios compares two quantities by relating them through division, gave real-world examples of ratios (e.g. rice to water), demonstrated that Hooke's Law and Newton's Second Law follow the same structure, and showed that many other scientific formulas also depend on ratio structure. Students went through the direct instruction materials at their own pace and could take notes if they wanted.

Measures

Uncertainty

I designed my measure of uncertainty to reflect Yu and Dayan's (2005) definition of uncertainty: a lack of information about the environment to make decisions about it (see

Appendix C). Items for this measure were adapted from two surveys that most closely reflected this definition (Power, Denisova, Papaioannou, & Cairns, 2017; Abelson, Tripp, Brouwers, Pond, & Sussman, 2018). On this measure, participants responded to statements such as, "I felt uncertain during the activities I did today" and "I was sure about the activity as I was doing it today (reverse coded)," on a scale from 1 (Strongly Disagree) to 5 (Strongly Agree). Internal consistency of this measure was good (Chronbach's alpha day 1 = .78, day 2 = .80).

Curiosity

Self-report.

State-level cognitive curiosity was measured quantitatively with an eight-item Likert scale questionnaire adapted from the state subscale of Naylor's (1981) State-Trait Curiosity Inventory (See Appendix A). Participants responded to statements such as, "I want to know more about what I just worked on," and "I feel like seeking information about what I just worked on," on a scale of 1 (strongly disagree) to 4 (strongly agree). The final curiosity score was the mean response on all eight items. Internal consistency of this curiosity measure was good (Chronbach's alpha between .73 and .81).

Behavioral.

While my previous study allowed us to measure curiosity quantitatively via self-report, I lacked behavioral and qualitative information about students' curiosity. To address that in this new study, I developed a measure where students could track what they were curious about, rather than simply how curious they were. For this measure, students listed any questions they had. These could be about how far a spring moves (on Day 1) or the rate at which an object speeds up (on Day 2), questions about what they were supposed to do, or any other questions they had (See Appendix B). I tallied and categorized the questions based on a coding manual I

developed using constant comparative methods for data analysis (Glaser & Strauss, 1967) to identify themes in students' questions. Based on the data, three clear categories of questions emerged: (1) content, (2) process, and (3) other. Two trained coders categorized each of the questions into one of these three categories. Inter-rater reliability was high (kappa = .86). In cases where disagreements occurred, coders met and came to an agreement based on definitions in the coding manual. Table 8 shows the definitions of these categories, along with several real examples of questions students asked.

Table 8. *Definitions and Examples of Categories of Questions Students Asked*

Category	Definition	Example
Process	Questions or comments about how to solve the particular task at hand, their participating in the study, or what numbers they're supposed to use. These are questions that focus on *HOW* to do the tasks or determine the correct answer (what strategy, what tool, etc.).	"How do we find the object's speed rate?"
Content	Questions or comments about the specific content they learn in the study. These are questions that focus on *WHAT* the tasks are teaching them (Hooke's Law, Newton's 2nd Law, Ratios, "Types of Science", formulas, types of formulas, springs, forces, spring constant, mass, acceleration, area formula, difference in temperature formula, etc.). These include questions asking for clarification of the content.	"Does the more force you place on the spring make it go farther?"

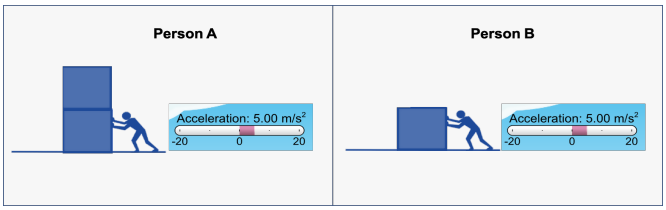
Other	Miscellaneous questions or comments that don't fit into Process or Content. These include questions about why they are learning what they are learning, expressions of confusion, and questions about our study that are not about what they're learning.	"Why does this frustrate me?"

Learning Pretest and Posttest

The learning pretest/posttest included four questions that assessed procedural and conceptual understanding of Hooke's Law and Newton's Second Law formulas (see Appendix D). The procedural items were originally published in Lamnina and Chase (in press), and the conceptual items were developed specifically for this study. These items are similar to the learning contexts (i.e. the activities students complete) and tested the same concepts taught in the Hooke's Law and Newton's Second Law videos. The test also included distractor items unrelated to the concepts to be taught. The distractor items required students to subtract or multiply, rather than divide. I included these items so that students would not simply assume that they were to divide on every problem I gave them during the study, but these items were not analyzed. There were two isomorphic versions of this test, which were counterbalanced. All items were scored as shown in Table 9 and averaged to compute a learning score on pretest and posttest. Two coders coded 25% of the data and achieved strong reliability (kappa = .95). After resolving disagreements in the initial 25% of the data, each coder coded half of the remaining data. I did not compute alpha for this measure because it would not be meaningful, given the test contained only 4 items that differed in both the content and knowledge type they assessed (see Tavakol & Dennick, 2011).

Table 9. *Learning Items with Scoring Rubric*

	Sample Procedural Learning Item	Sample Conceptual Learning Item
0 points	Responded with something other than	Selected Choice B or C

	Sample Procedural Learning Item	Sample Conceptual Learning Item
	A force of 10 Newtons moves a spring with a spring constant of 30 N/cm. How far does the spring move?	The people are pushing the boxes to make the boxes accelerate.  Which of the following statements is true? a. Person A is pushing the box harder. b. Person B is pushing the box harder. c. The people are pushing the boxes equally hard. Explain your answer.

	what is listed under ".5 points" or "1 point"	
.5 points	Divided in reverse (e.g. "3")	Selected Choice A but did not have an explanation that related mass and force as a ratio.
1 point	Correctly solved the problem (e.g. "1/3")	Selected Choice A and had an explanation that related mass and force as a ratio.

Transfer Posttest

The transfer posttest included three questions (from Schwartz, Chase, Oppezzo, & Chin, 2011, and Lamnina & Chase, in press, see Appendix E) that tested whether students could correctly apply and adapt ratio structures to novel contexts. While learning test items assessed information that was taught directly to students (e.g. Newton's and Hooke's laws), transfer questions differed either in context or in both content and context (Barnett & Ceci, 2002).

Specifically, two transfer items tested if students could transfer the taught formulas to different contexts (i.e. Hooke's Law applied to pictures of trampolines being stretched, rather than springs being pulled), and one item tested whether students could transfer a principle (i.e. ratio structure) from the taught knowledge domain (i.e. Hooke's Law, Newton's Second Law) to a novel knowledge domain (e.g. concentration). This question required students to invent a new ratio-based formula and apply it to four examples (see Figure 8); students needed to use their knowledge of ratio structures to determine the concentrations of four cups of chocolate milk. Hooke's Law or Newton's Second Law would not help students solve this kind of question, but transferring knowledge of the ratio structure from the previously learned formulas would. To

solve this problem correctly, students needed to find the ratio of cocoa powder to milk for each cup. All three transfer questions required students to apply formulas to four examples each. Students received up to four points for each of these questions, one for each example correctly solved. These were then scaled to a 0-1 score. Two coders coded 25% of the data and achieved strong reliability (kappa = .97). After resolving disagreements in the initial 25% of the data, each coder coded half of the remaining data. I didn't compute alpha for this measure because it would not be meaningful, given the test contained only 3 items (see Tavakol & Dennick, 2011).

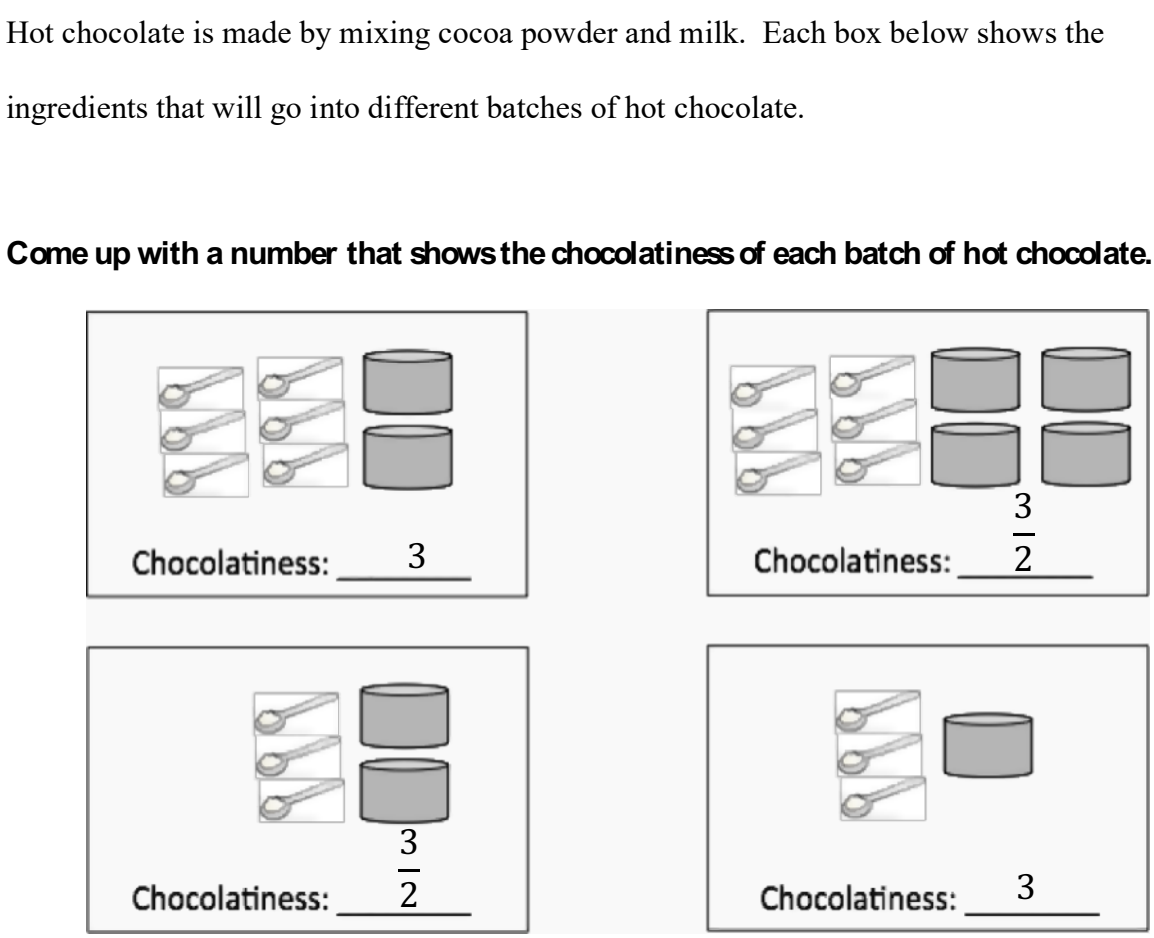


Figure 8. Sample transfer item and solution.

Process Variables During Invention and Direct Instruction

To assess differences in the Invention process between the HU and LU groups, I counted the number of invented solutions (e.g. iterations), which is often associated with learning outcomes after Invention tasks (e.g. Kapur, 2014) The activity booklets in which students were inventing were designed so that each new iteration was written on a new page. Therefore, I counted the number of pages used as a measure of number of iterations. In addition, I counted how many times the student correctly invented the target formula (0, 1, or 2).

I further examined process variables during direct instruction. Specifically, I recorded whether students took notes and, using a built-in timer, timed how long they spent reviewing the reading materials.

Results

I analyzed my data with ANOVA and regression models. Preliminary analyses suggested that students' honors status and pretest scores had effects on my outcome variables, while grade, class, and teacher did not. I, therefore, controlled for honors status and pretest scores in all my analyses.

Uncertainty

To assess the success of my uncertainty manipulation, I examined differences in reported uncertainty between groups. I found that students in the high uncertainty group felt significantly more uncertain than those in the low uncertainty group on both days of instruction, according to results of a repeated measures ANCOVA of condition and day on uncertainty, $F(1, 204) = 8.85$, $p = .003$, $\eta p^2 = .04$. Averaging across both days, the HU group reported uncertainty scores that were .27 points higher than the LU group, $d = .36$. Table 10 shows descriptive statistics for both conditions on both days. Overall, students felt less uncertain on the second day of instruction,

compared to the first, $F(1, 204) = 6.37$, $p = .012$, $\eta p^2 = .03$. There was no significant day by condition interaction ($p = .41$). Neither honors status nor learning pretest had significant effects on uncertainty (p's > .38).

Table 10. *Means and Standard Deviations of Uncertainty for Each Group*

Measure*	High Uncertainty (n=97)		Low Uncertainty (n=111)	
	M	SD	M	SD
Uncertainty Day 1	3.28	.75	3.02	.83
Uncertainty Day 2	3.22	.85	2.88	.78

Curiosity

Survey.

To test for condition effects on curiosity and changes in curiosity over time, a repeated measures ANCOVA was conducted, with the five time points of measurement as a within-subjects factor, condition as a between-subjects factor, and curiosity score as the dependent variable. Honors status did not have a significant effect ($p = .406$), but learning pretest did (p = .012). Overall, students in the HU group reported greater curiosity than students in the LU group, $F(1, 204) = 5.72$, $p = .027$, $\eta p^2 = .02$. There was also a significant main effect of time, $F(4, 792) = 11.08$, $p < .001$, $\eta p^2 = .05$. Finally, there was a significant interaction of condition by time, $F(1, 204) = 8.85$, $p = .003$, $\eta p^2 = .04$, such that HU reported more curiosity than LU (p's < .015) at Times 1, d = .44, and 2, d = .40, but by the third measure, these differences disappeared (p's > .069). Simple effects of time were significant for the HU group, $F(4, 201) = 15.93$, $p < .001$, $\eta p^2 = .24$, and for the LU group, $F(4, 201) = 6.62$, $p < .001$, $\eta p^2 = .12$. For both the HU and LU

groups, all time points were significantly different from each other, *p*'s < .05, except T3 and T4, p's > .10. In sum, curiosity generally declined over time in both groups, and the HU group reported feeling more curious by an average of .24 points on Day 1 (T1 and T2) than the LU group, a medium-sized effect, *d* = .48. Figure 9 shows the pattern of results quite clearly.

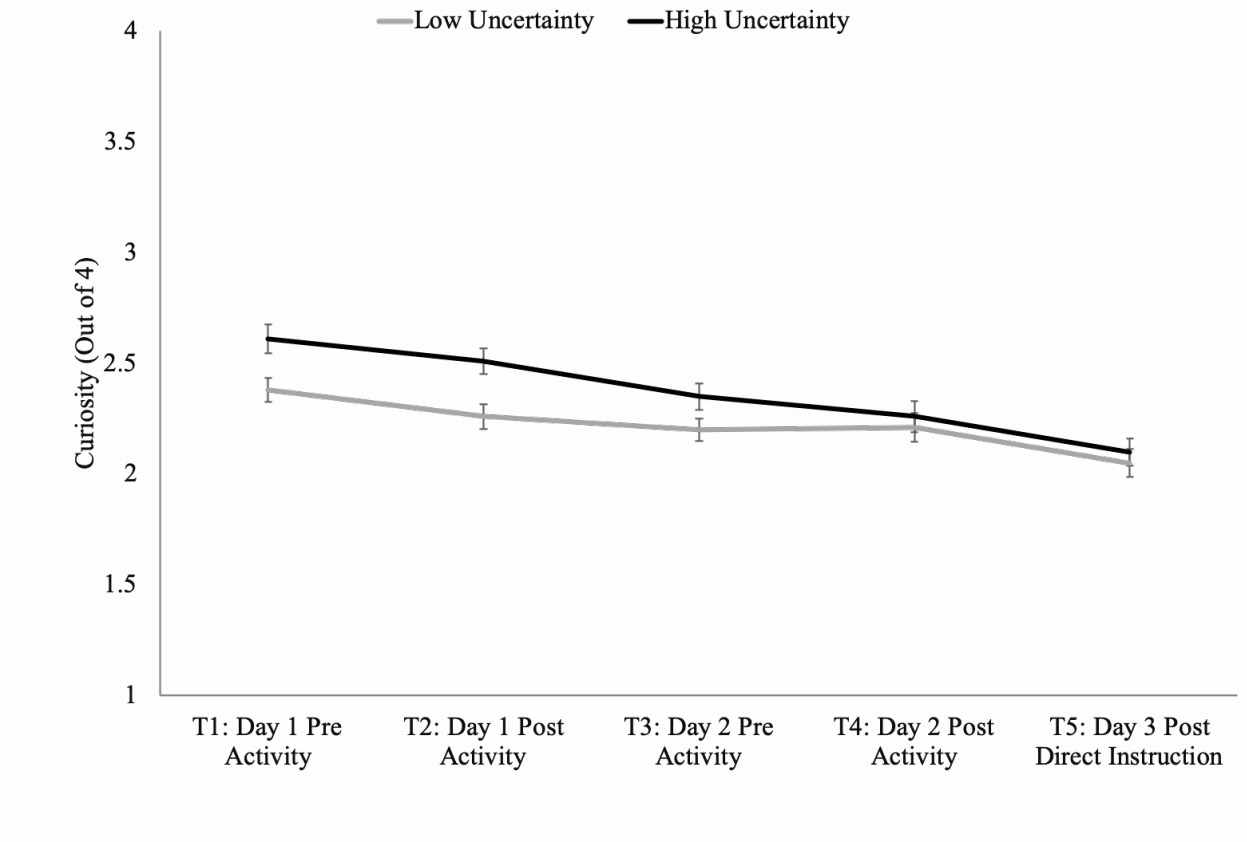


Figure 9. Curiosity over time by condition. Error bars represent +/- 1 SE.

Behavioral.

Students in the high uncertainty group asked almost twice as many process questions as those in the low uncertainty group, *d* = .33, but a similar number of questions in the "content" and "other" categories (see Figure 10). These results were obtained from a repeated measures MANCOVA of condition and day on the log transformed number of Content, Process, and Other questions asked. Overall, there was a near-significant effect of condition, $F(3, 202) = 2.58$, p =

.055, ηp2 = .03. Follow-up tests of between subjects effects revealed a significant difference in number of process questions asked, $F(1,204) = 4.33$, $p = .039$, $\eta p^2 = .02$, but not in number of content or other questions asked, $p > .191$. There was also a significant main effect of day, $F(3, 202) = 8.18$, $p < .001$, $\eta p^2 = .11$, with students asking significantly more questions on the first day than on the second. There were no significant effects of the interaction of day by condition, $p = .594$, honors status, $p = .306$, or pretest score, $p = .744$.

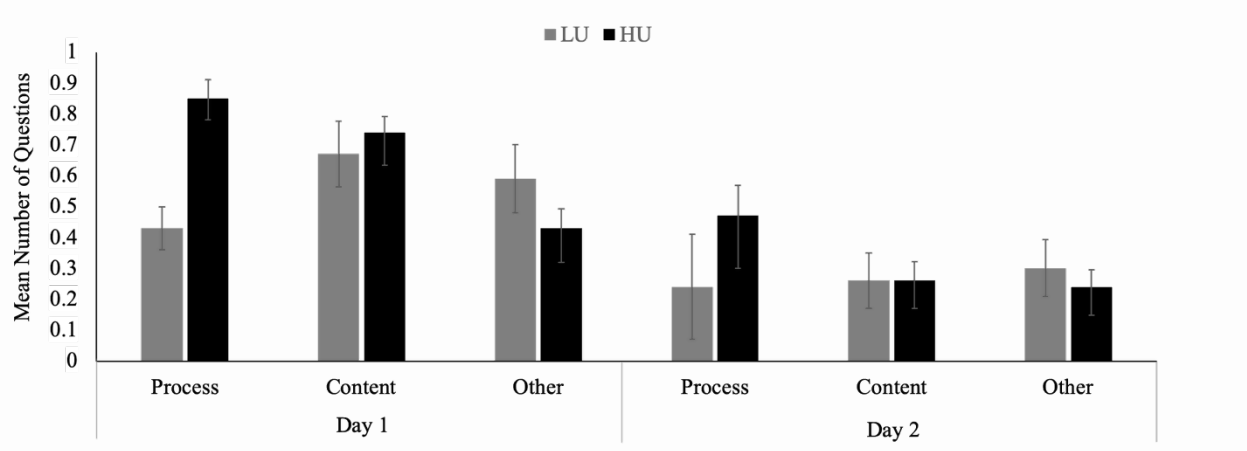


Figure 10. Means of number of questions asked. Error bars represent +/- 1 SE.

Learning Pretest to Posttest

An initial ANOVA revealed no differences in learning pretest scores between conditions $F(1, 205) = 1.77$, $p = .184$, indicating that both conditions had similar levels of prior knowledge. A repeated measures ANOVA, showed that all conditions learned from pretest to posttest, $F(1, 205) = 83.29$, $p < .001$, $\eta p^2 = .29$, with an average gain of .13 points, a 49% increase, $d = .65$. However, there were no differences between conditions at posttest, $F(1, 205) = 1.77$, $p = .184$, ηp2 = .01, nor a significant condition by day interaction, $F(1, 205) = 2.29$, $p = .132$, $\eta p^2 = .01$. Honors status did not have a significant effect on learning, $p = .693$. See Figure 11.

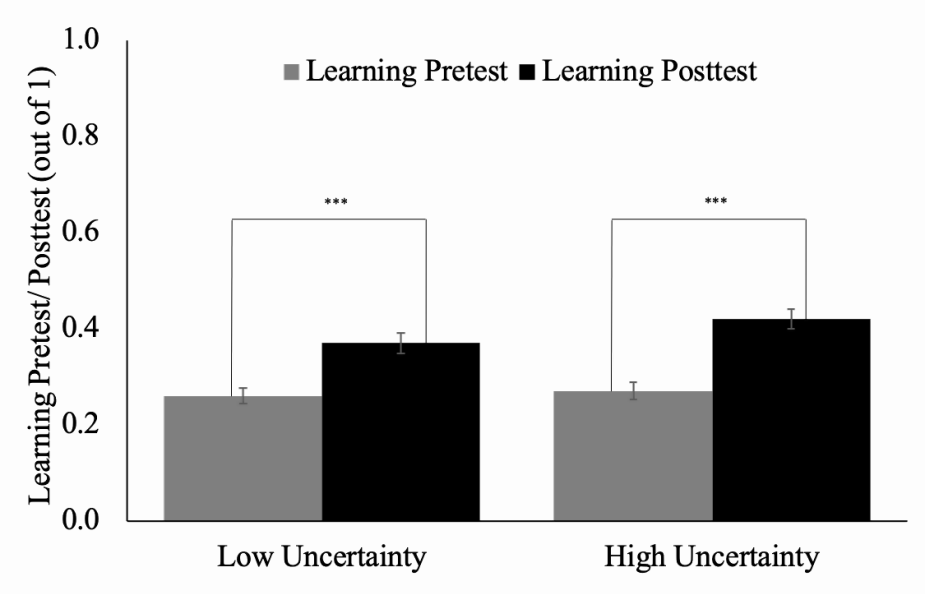


Figure 11. Learning. *** Significant at p <.001. Error bars represent +/- 1 SE.

Transfer Posttest

The HU group transferred more than the LU group as revealed by an ANCOVA, $F(1, 204) = 4.62$, $p = .033$, $\eta p^2 = .02$. On average, the HU group scored .11 more points on the transfer posttest than the LU group (see Figure 12). Honors status and learning pretest both had significant effects on transfer (p's < .01).

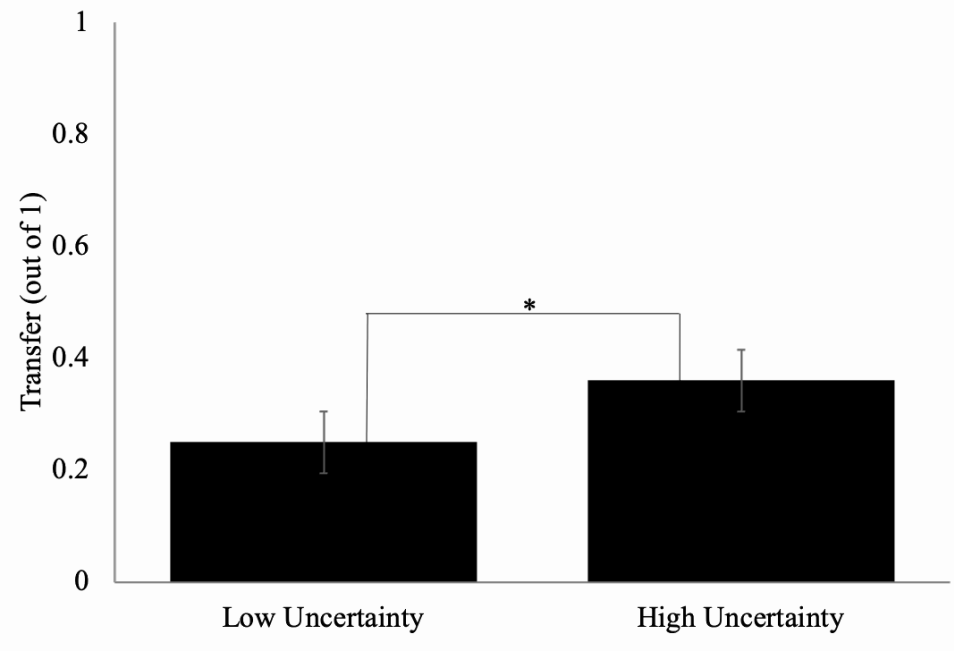


Figure 12. Transfer scores. * Significant at p <.05. Error bars represent +/- 1 SE.

Process Variables During Invention and Direct Instruction

I conducted exploratory analyses to see whether different levels of uncertainty impacted learning processes. I found that groups did not differ in either the frequency of iterations (e.g. invented formulas) or the number of correct formulas invented (Table 11). An ANCOVA revealed that the number of iterations made by the HU group was similar to the number of iterations made by the LU group, $F(1, 204) = 2.77$, $p = .098$. Neither honors status nor pretest score affected the number of iterations students came up with, p's > .165. Further, an ordinal regression predicting the number of correct solutions (0,1, or 2) showed no differences between the HU and LU groups, $B = .30$, Wald = .83, $p = .361$. Pretest score positively predicted the number of correct solutions students invented, $p < .001$, but honors status did not have a significant effect, $p = .276$.

Groups also did not differ during direct instruction, in terms of time spent reading the materials and whether students chose to take notes (Table 11). The same proportion of students

in the HU and LU groups took notes (86%). Further, an ANCOVA revealed that time spent reading the materials did not differ between groups, $F(1, 203) = .28$, $p = .598$. Neither honors status nor pretest score had a significant effect on time spent reading, p's > .062. Predictors of

Table 11. *Descriptive Statistics of Learning Process Variables*

	Number of Iterations		Number of correct solutions (% students)			Note-taking (% students)		Minutes Spent Reading	
	M	SD	0 correct	1 correct	2 correct	Notes	No Notes	M	SD
LU	3.81	2.25	69%	29%	2%	86%	14%	9.76	5.82
HU	3.39	1.51	76%	21%	4%	86%	14%	10.01	5.83

Predictors of Learning

To examine predictors of learning, I ran three linear regression models, in a hierarchical fashion. In the first model, I regressed learning posttest on my control variables of honors status and pretest score. The overall model was significant. Next, I added curiosity to the model, using the mean of the first four measures of curiosity, since I did not expect groups to differ by the fifth measure given after direct instruction. Surprisingly, this did not explain additional variance, and curiosity did not predict learning, $\beta = .56$, $t(3,204) = .36$, $p = .720$. Finally, to test whether the effect of curiosity on learning differed by condition, I added condition and the condition by curiosity interaction as predictors, and found that this model did not explain additional variance.

Predictors of Transfer

To examine predictors of transfer posttest, I ran the same regression models as for learning posttest, but with transfer as the outcome variable. Again, I found that the first model of control variables only was significant. I then added curiosity to the model. Again, this did not explain additional variance and did not predict transfer β = -.03, t(3,204) = -.37, p = .709,. When I added condition and the condition by curiosity interaction to the model, I found that the new model explained significant additional variance. Mirroring my significant condition effects on the transfer test, condition significantly predicted transfer, β = .15, t(5,202) = 2.23, p = .027, but the interaction of curiosity by condition did not.

Discussion

As predicted in my first hypothesis, students in the HU group reported more uncertainty and more curiosity overall than students in the LU group. As students progressed in the study and gained more information, both uncertainty and curiosity decreased. By the third of five survey measures of curiosity, groups no longer showed significant differences. This suggests that gaining information satiates curiosity. This is further supported by my behavioral measure of curiosity, in which I asked students to list any questions they had. With this measure, I also found that the number of questions significantly decreased by the second day of invention. Additionally, exploratory analysis of the questions students asked revealed that the HU group generated a significantly higher number of questions about the process. This makes sense because I manipulated process-related information between groups.

While all students showed significant learning gains from pretest to posttest, there were no differences in learning between groups, which runs contrary to my prediction. This is surprising because research suggests that uncertainty should lead to curiosity, thereby fostering

learning. However, even though groups differed in both uncertainty and curiosity, these did not translate to differences in learning. This could be because overall, the groups were nearly identical. Apart from two two-minute videos, the groups completed the same exact activities. They even completed them with the same quality in terms of number of iterations generated and number of correct solutions found during invention. Further, groups were equally likely to take notes during direct instruction, suggesting equal levels of effort. Perhaps the magnitude of differences between groups was not enough to result in differences in learning.

However, when it came to transfer, students in HU performed better than students in the LU group, in line with my second hypothesis. This suggests that smaller changes in uncertainty might be enough to influence transfer, even if they are not enough to influence learning. A potential reason for this is that transfer reflects deeper learning (Bransford et al., 2000), and while differences in basic learning may be subtle, differences in deeper learning are more readily detectable.

While I found differences in curiosity between groups, I did not find support for my third hypothesis that curiosity predicted learning or transfer. This is surprising because theory suggests that curiosity should influence learning. Additionally, previous research suggests that curiosity should be beneficial for learning, given that curiosity has been shown to positively influence recall (e.g. Arnone et al., 1994; Ainley et al., 2002) and test scores (e.g. Alberti & Witryol, 1994; Shah et al., 2018; von Stumm et al., 2011). However, this previous research focused on trait curiosity, not state curiosity, which is what I measured in this study. Perhaps, state curiosity does not influence learning to the same extent. In fact, another study (Lamnina & Chase, in press) examining whether state curiosity predicted learning, also found null results.

The result showing that curiosity did not predict transfer is even more surprising, however, because in a previous study teaching the same content, data show that curiosity, using an identical measure, did, in fact, predict transfer (Lamnina & Chase, in press). A potential reason for this discrepancy is that there was a wider range of curiosity scores in the previous study, compared to the current one. Therefore, this null result might be due to a restriction of range. Additionally, this population, overall, had lower curiosity and transfer scores, compared to the participants in Lamnina and Chase (in press). It's possible that for this population, the relationship between curiosity and transfer is different. Although, it is unclear why the relationship would differ and further research on individual differences could help elucidate this.

Another possibility is that uncertainty influences transfer directly, rather than through curiosity. Transfer situations are highly uncertain situations. By definition, transfer situations are novel with respect to the initial learning situation. On the surface, they do not appear to have a clear relationship with prior learned material. Thus, learners are likely to feel some uncertainty when posed with a transfer problem. It is possible that the high uncertainty group learned to cope with this uncertainty, and this enhanced their ability to solve uncertain transfer problems. This possibility could be tested in future research.

Additionally, a possible reason why the HU group might have transferred more is that they reaped more benefits from the invention task. Students in the HU group needed to realize the value of quantifying variables and relating them through math, since this information was not given to them. Given that the transfer items do not actually prompt students for formulas, or even numbers, it is possible that this realization that precise math could solve these problems helped the HU group transfer.

Finally, perhaps the uncertainty survey used as a manipulation check in this study had low construct validity. It could be that items such as, "I had enough information to complete the activity today," were not reflective of uncertainty as I designed them to be. Future work can test if this survey correlates with other related measures to get more information on its validity.

Implications

Taken together, these findings contribute to practice, instructional design, and educational psychology literature. First, while prior research has examined the connection between uncertainty and curiosity and between curiosity and learning, to my knowledge, little work explored this connection in classroom settings where content learning is considered. Research that does examine the effect of curiosity on learning or academic achievement tends to conceptualize curiosity as a trait, rather than a malleable state that can be influenced with instruction. Additionally, prior research tended to focus on straightforward tasks, rather than complex exploratory learning experiences. The present work addressed these gaps and provided support for the use of highly uncertain instruction in the classroom, suggesting that uncertainty can enhance curiosity when initially presented. I also demonstrated how levels of uncertainty can be manipulated within exploratory learning tasks, rather than simple tasks such as pressing a button, and how such manipulations influence state-level curiosity. Further, rather than measuring curiosity once, I took multiple measurements, allowing us to observe how curiosity changed over time. I showed that as students received more information, and eventually all the information via direct instruction, their curiosity was satiated, as suggested by the decrease in curiosity over time.

Additionally, I contributed to research on curiosity by developing a new behavioral measure of cognitive curiosity by giving students the opportunity to ask as many or as few questions as they liked. Since this was done privately on students' individual laptops, this measure did not suffer from conflation with social factors, as is the case with other behavioral measures. It also allowed us to assess students' curiosity qualitatively, so I could hone in on the specific questions about which they were curious. Such information is useful for designing instruction for curiosity, since knowing what students are curious about can guide designers in deciding which information to withhold when inducing uncertainty.

Moreover, this study contributes to research on uncertainty. Specifically, my data show that high uncertainty leads to greater transfer. This is important, since transfer is rare (Gick & Holyoak, 1983). To my knowledge, almost no research on uncertainty has taken transfer into account; it has focused almost exclusively on direct learning. Yet, in my study I found that while all students learned equally well from pretest to posttest, those in the high uncertainty group showed greater transfer.

Limitations and Future Directions

While there were many promising results in this study, this research has several limitations and questions for future work to address. First, while I compared two levels of uncertainty, the ideal level of uncertainty in a classroom is still unclear. Theory suggests that the relationship between uncertainty and curiosity is an upside-down u-shape, such that the highest level of curiosity occurs at a level of uncertainty that is not too high or low. Future work can compare more nuanced levels of uncertainty to get a better understanding of what that point is. Further, as expected, curiosity reduced as more students obtained more information. Thus, it appears that uncertainty provokes curiosity only when initially presented. This could reflect

information satiating students' curiosity, and with each new "uncertain" lesson curiosity may be restored. However, the current study does not have data to support this, and questions about how to maintain curiosity over time remain. Specifically, future research should test if repeatedly presenting students with this type of instruction would lead students to learn to expect it, diminishing the effect of instruction on curiosity. This research can include case studies with longitudinal data to contribute to an understanding of how uncertain instruction affects curiosity, learning, and transfer long-term.

Conclusion

I gave two groups of students highly uncertain instruction in the context of science learning by instructing them to invent formulas before giving them direct instruction. I varied level of uncertainty between groups by giving one group task-relevant information that would help them solve the problem (low uncertainty) and one group task-irrelevant information (high uncertainty). This revealed that high uncertainty in science instruction increases curiosity initially and leads to more transfer of learned concepts to novel contexts. However, more work needs to be done to find the optimal level of uncertainty, uncover the mechanism of uncertainty leading to increased transfer, and determine ways to maintain curiosity over time.

Chapter 4: Overall Discussion

Picture a classroom full of curious learners. The teacher is giving an astronomy lesson. The students, hungry to learn, excitedly raising their hands to ask questions about how the moon orbits the earth or why some planets have many moons and we have only one. The bell rings, ending the class, and students who did not get their questions answered groan disappointedly. They walk out of the class discussing the lesson with one another. A particularly curious student rushes to his locker to get his phone and searches for more information. Intuitively, it seems that students like those in this vignette are likely to learn more information and learn it more deeply than students who are aiming to memorize just enough information to pass a test. Unfortunately, the latter scenario appears to occur more often than the former. Educators and educational researchers are aware of this, as evident by the countless articles and blog posts on the topic of making kids more curious and how curiosity is scarce in the classroom, along with the explicit call to foster curiosity written in many educational standards.

The research presented in this dissertation aims to address this issue empirically and provide some ideas and guidance for how to create curiosity-provoking learning environments. Theoretical descriptions of curiosity (e.g. Berlyne, 1954, Dashiell, 1925; Erikson, 1950; Hebb, 1955; James, 1950; Loewenstein, 1994; Piaget, 1952) along with several empirical studies (e.g. Berlyne, 1962; Boykin & Harackiewicz, 1981; Fisher, HirshPasek, Newcombe, & Golinkoff, 2013; Hsee & Ruan, 2016; Loibl & Rummel, 2014; Markey & Loewenstein, 2014; Newcombe, & Golinkoff, 2013; Weisberg, Hirsh-Pasek, Golinkoff, Kittredge, & Klahr., 2016) all agree that uncertainty is one factor that consistently promotes curiosity. However, little work has been done to test this in real-world classrooms, especially when using inherently uncertain exploratory instruction. Additionally, most the findings I have regarding curiosity's influence on learning and

academic achievement focus on trait-level curiosity. While this research is useful in my understanding of the relationship between curiosity and learning, it will not necessarily provide beneficial information to an educator trying to influence curiosity, that is, curiosity at the state-level.

In two studies, I demonstrate two methods of doing this. In the first study, I show that Invention, an inherently uncertain form of instruction, led to more curiosity compared to a traditional tell-then-practice pedagogy. The groups in these studies completed the same problems in the same amount of time, but the group that received direct instruction *after* problem solving became more curious. In the second study, I show that uncertainty can further be manipulated within Invention. In this study, both groups did not receive direct instruction on the instructional content until after they invented. However, one group received some problem-relevant information about their target response and the process of arriving at the correct answer, and one group received problem-irrelevant information. The group that did not receive information about their goal or the process of getting to it experienced higher uncertainty. They also, as expected, experience greater initial curiosity. My second study also added to the findings of the first study by measuring curiosity behaviorally, as well as with a survey. By doing this I showed that students not only reported greater curiosity, but also acted more curious, as quantified by the number of questions asked. Taken together, these studies show that uncertainty, induced by initially withholding information, is beneficial for curiosity.

However, I must also ask if this curiosity will, as assumed, influence learning. In both studies, I show that all groups learn from pretest to posttest. However, higher uncertainty groups learned as equally well as lower uncertainty groups. It was not until I observed how well students *transferred* their knowledge did I see differences between the groups. In terms of transfer, groups

that experienced more uncertainty (the Invention groups in Paper 1 and the group that received task-irrelevant information in Paper 1) scored higher than groups that experience less uncertainty (the tell-then practice group in Paper 1 and the group that received task-relevant information in Paper 1). These findings are different from what is suggested by other research, which demonstrates that uncertainty causes curiosity and that curiosity causes learning. However, to my knowledge, research on uncertainty and curiosity largely ignores transfer and focuses only on learning. Additionally, I found no studies consider all three variables (uncertainty, curiosity, and learning) in combination. This could be because research connecting curiosity and learning tends to overlook state-level curiosity, which is the kind of curiosity measured in research connecting uncertainty and curiosity. Yet, my research suggests that uncertainty in instruction, used to increase state-level curiosity, matters only when it comes to the deeper learning needed for transfer, and not when it comes to direct procedural or conceptual learning.

I also directly tested the notion that curiosity itself promotes learning. In both studies, I found that curiosity did not predict learning. This is in line with my finding that there were no differences in learning between groups (i.e. uncertainty did not influence direct learning) but is admittedly counterintuitive. I further examined if curiosity predicted transfer. Here, I found some inconclusive results between the two studies. In the first study, I found that curiosity significantly predicted transfer but not above and beyond the influence of condition. In the second study, I found that curiosity did not predict transfer at all. There are a few reasons why this could have occurred. Some possibilities are that I might have had a restriction of range problem in curiosity or had low construct validity of my uncertainty measure in my second study. However, it is also possible that the effect that uncertainty has on transfer is mediated by a variable other than curiosity, or it is direct rather than mediated. This would explain not only why I did not find that

curiosity predicts transfer in the second study, but also why curiosity did not predict transfer above and beyond condition in my first study. These discrepancies between my two studies and between my studies and previous research leads to many interesting questions for future research: Does state-level curiosity influence learning or does only trait-level curiosity matter? Does state-level curiosity truly affect transfer or is transfer more readily influenced by uncertainty? If so, why? Is there a mediator between uncertainty and transfer or is this a direct effect? This research provides support for uncertain instruction, as it increases both curiosity and transfer but uncovers a lot of avenues for future work to explore.

Some other contributions of this work include assessing the effect of uncertainty on affect and observing how uncertainty and curiosity change over the course of instruction. Specifically, in my first study I address the possibility that while uncertainty can have desirable effects, it may also be detrimental to affect, since uncertainty is often perceived as a negative state. I demonstrate that by giving students expectations of uncertainty, I can reduce students' levels of negative affect to be similar to levels of negative affect reported by students who experienced no uncertainty. Moreover, I show that affect matters for learning. Particularly, in my first study, positive affect positively predicted learning.

Further, in study in my second paper, I show that as students progress through a lesson, their uncertainty declines. This suggests that students gain more information throughout the lesson. Further, I show that their curiosity also declines, suggesting that it is satiated with the information they gain. In this study, I also examine curiosity qualitatively. That is, not only do I test how curious students are, I explore what they are curious about. This provides information for instructional designers who are seeking to design instruction for curiosity. Specifically, I

show that in my study students were curious about both process and content, suggesting that uncertainty manipulations can focus on either of these aspects.

Overall, this work contributes to answering one persisting question that many educators have: How do I make my students more curious? It appears that one way is by designing instruction to be uncertain. This could be done by initially withholding some information about the content, the problem-solving process, or both. Doing so will not only make students more curious, it will also lead them to transfer more of what they learn from the subsequent direct instruction. This is incredibly encouraging. Yet, there are many more questions to be answered so that I can make the scenario in the first paragraph more commonplace. In addition to the two uncertainty manipulations I present here, what other ways can I design uncertain, curiosity-provoking instruction? What is the sweet spot of uncertainty, so that students are at the peak of their curiosity, without becoming too confused or frustrated? When is the best time to give direct instruction after uncertain instruction? What about individual differences – will certain student traits affect how they react to uncertainty? There is a lot more work to be done, but I am hopeful that soon enough there will be classrooms full of students excitedly exploring, seeking information, and learning driven by curiosity.

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Appendix A: Curiosity Survey

Several statements which people have used to describe themselves are given below. Read each statement and then select the number below the statement to indicate how you feel right now, that is, at this moment.

There are no wrong answers. Do not spend too much time on any one statement but give the answer which seems to describe how you feel.

(1) Not at all (2) Somewhat (3) Moderately so (4) Very much so

1. I want to know more about what I just worked on.
2. I feel curious about what I just worked on.
3. I am feeling puzzled by what I just worked on.
4. I want things about what I just worked on to make sense.
5. I am fascinated by what I just worked on.
6. I feel interested about what I just worked on.
7. I want to ask questions about what I just worked on.
8. I feel like seeking information about what I just worked on.

Appendix B: Behavioral Curiosity Measure

Questions about what I'm supposed to do:	Questions about how far a spring moves:	Other questions:

Appendix C: Uncertainty Survey

Several statements which people have used to describe themselves are given below. Read each statement and then select the number below the statement to indicate how strongly you agree or disagree right now, that is, at this moment.

There are no wrong answers. Do not spend too much time on any one statement but give the answer which seems to describe how you feel.

(1) Strongly Disagree (2) Disagree (3) Neither Agree nor Disagree (4) Agree (5) Strongly Agree

1. I felt uncertain during the activities I did today.
2. I was sure about the activity as I was doing it today.
3. I had enough information to complete the activity today.
4. I found today's activity confusing.
5. I didn't have enough information to complete the activity today.
6. I was unsure about the given information of today's activity in class.

Appendix D: Learning Pretest and Posttest

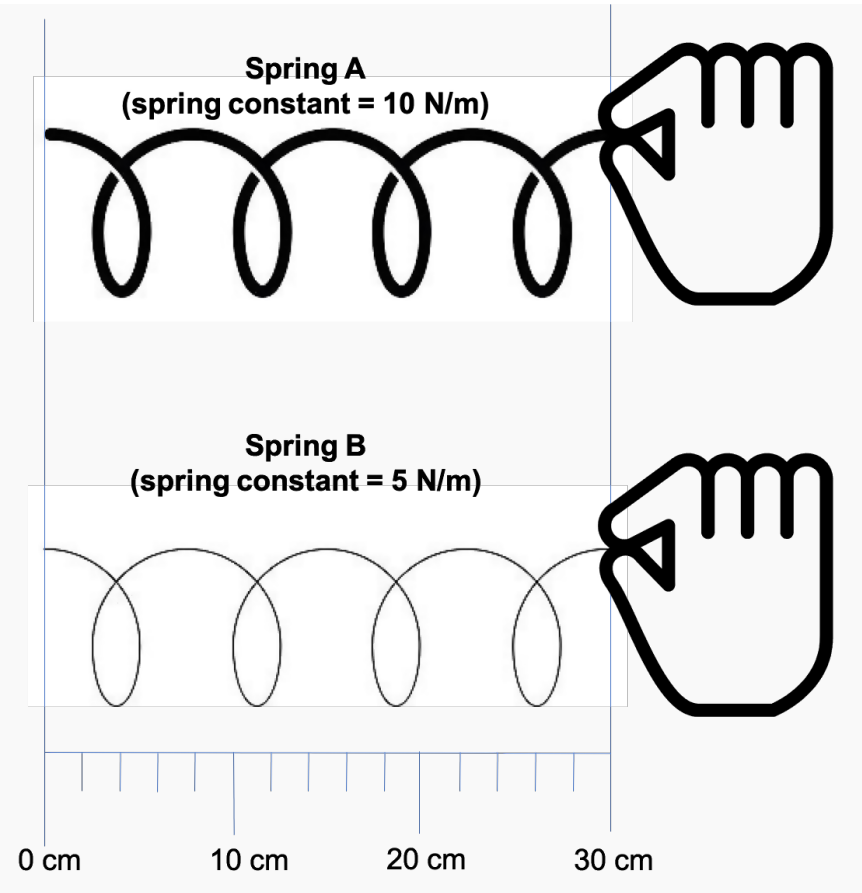
1. A plane is speeding up before it takes off. The plane has a mass of 9,000 kg and the force to accelerate the plane is 3,000 Newtons. What is the plane's acceleration? Show your work.

2. John wants to buy a new carpet for his bedroom. He measures that the room is 8 feet long and 10 feet wide. What is the area of the room? Show your work.

3. Christine and Helena are playing tug-of-war. Christine pulls the rope with a force of 100 Newtons. Helena pulls on the rope with a force of 80 Newtons. What is the total force applied to the rope? Show your work.

4. A force of 10 Newtons moves a spring with a spring constant of 30 N/cm. How far does the spring move? Show your work.

5a.



Hands are pulling each of the springs in the picture above. Which of the following statements is true?

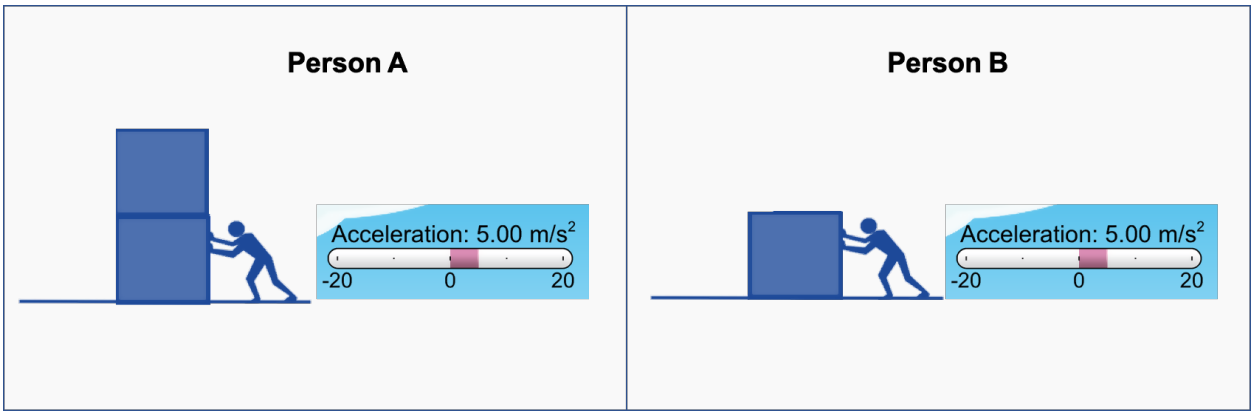
d. Spring A is being pulled harder.

e. Spring B is being pulled harder.

f. Spring A and Spring B are being pulled equally hard.

5b. Explain your answer.

6a.



The people are pushing the boxes to make the boxes accelerate. Which of the following statements is true?

g. Person A is pushing harder.

h. Person B is pushing harder.

i. Person A and Person B are pushing equally hard.

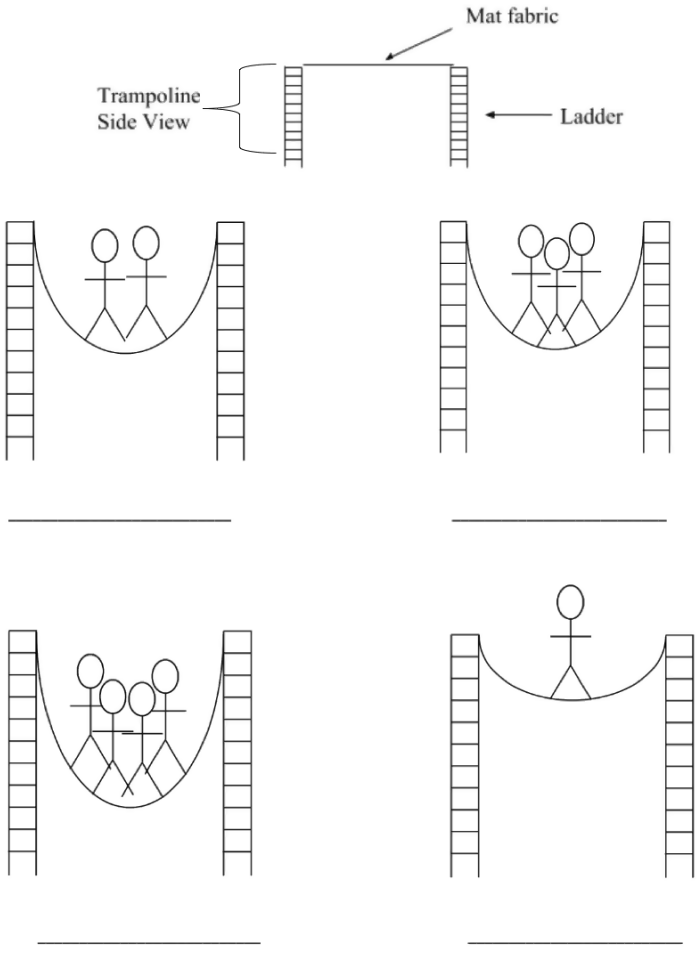
6b. Explain your answer.

Appendix E: Transfer Posttest

1a.

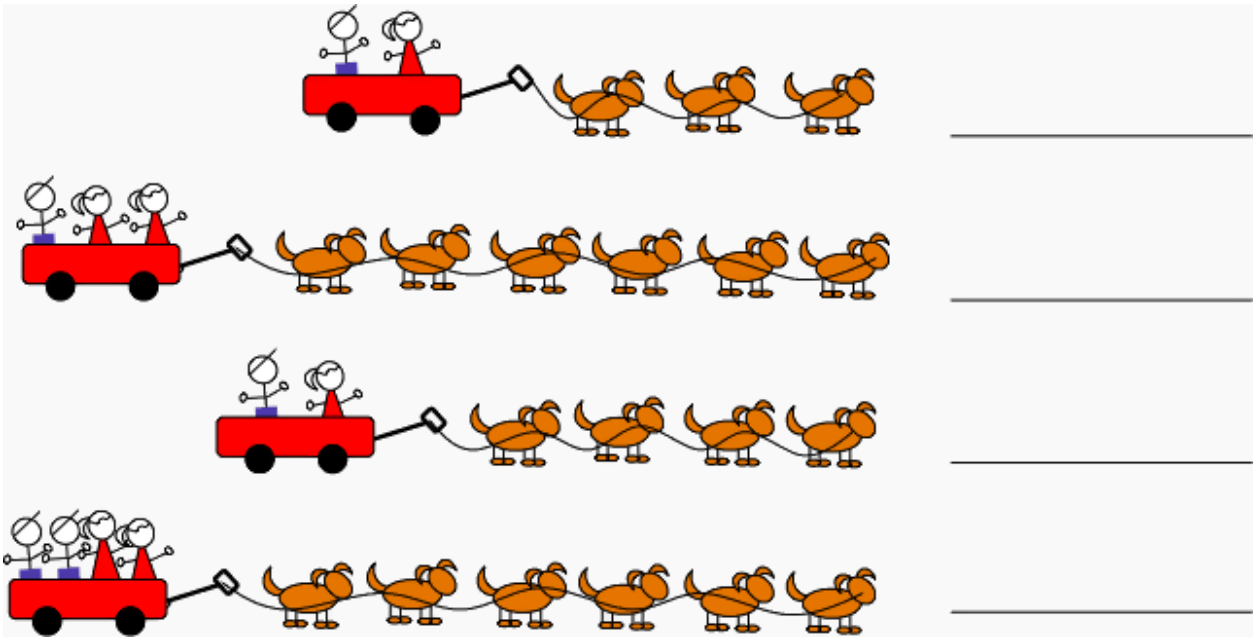
Trampolines are made with mats using different fabrics. Stretchy mats make the trampoline less bouncy.

Determine the <u>stretchiness</u> of the mat fabric for each trampoline. Write your answer on the line underneath each trampoline. **Show your work.**



2a. The neighborhood kids like to hook up their dogs to wagons and race. They all have the same type of wagon. **Show your work.**

Determine the rate at which each wagon team speeds up.



3a. Hot chocolate is made by mixing cocoa powder and milk. Each box below shows the ingredients that will go into different batches of hot chocolate.

Determine the chocolatiness of each batch of hot chocolate.